

# Data-driven Approaches to Identify the Regulators of the Anticancer Immune Response

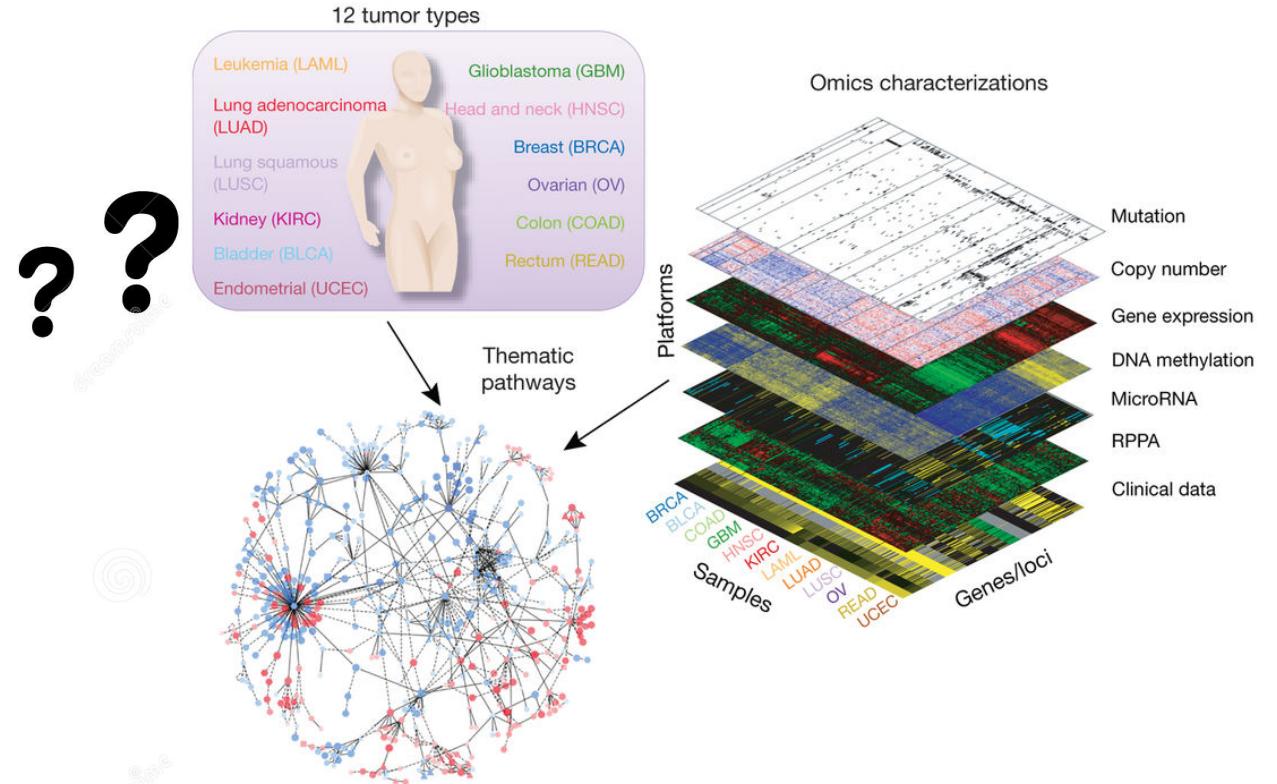
Peng Jiang, Ph.D.

July 9th, 2020

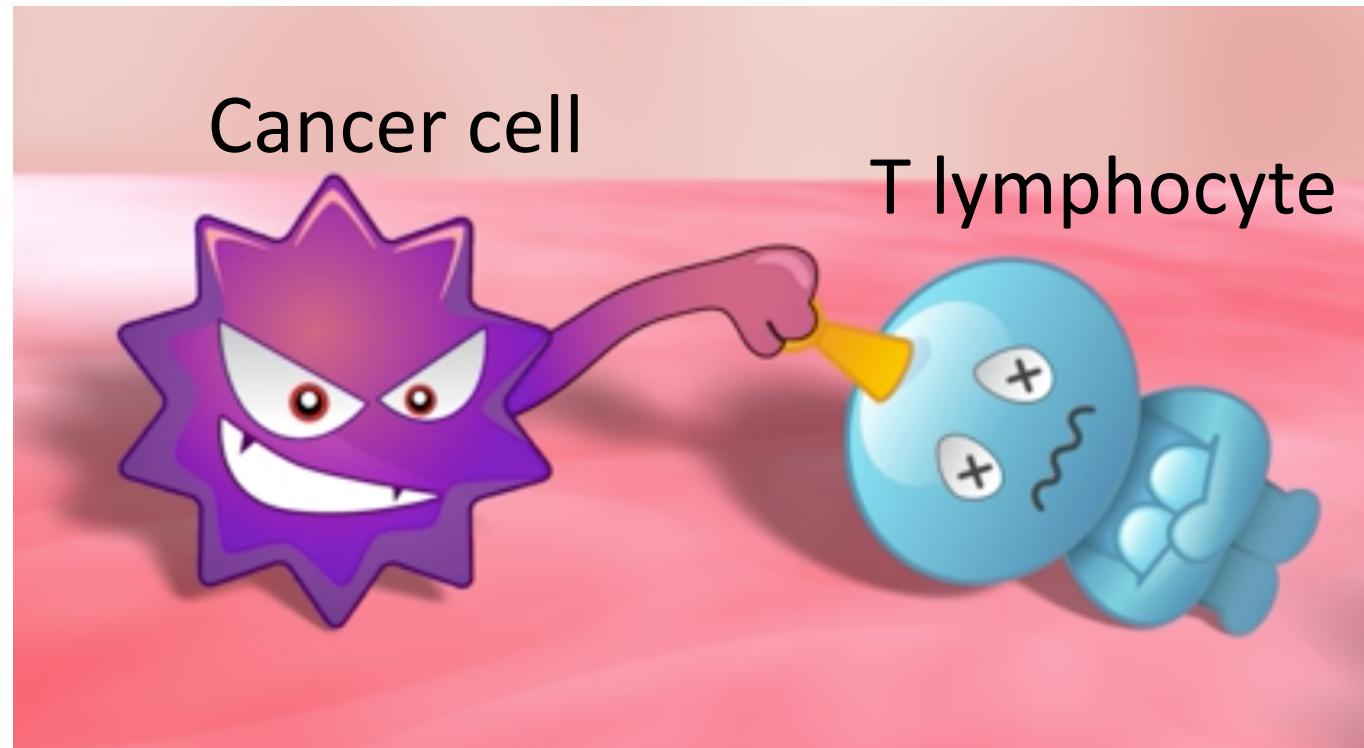
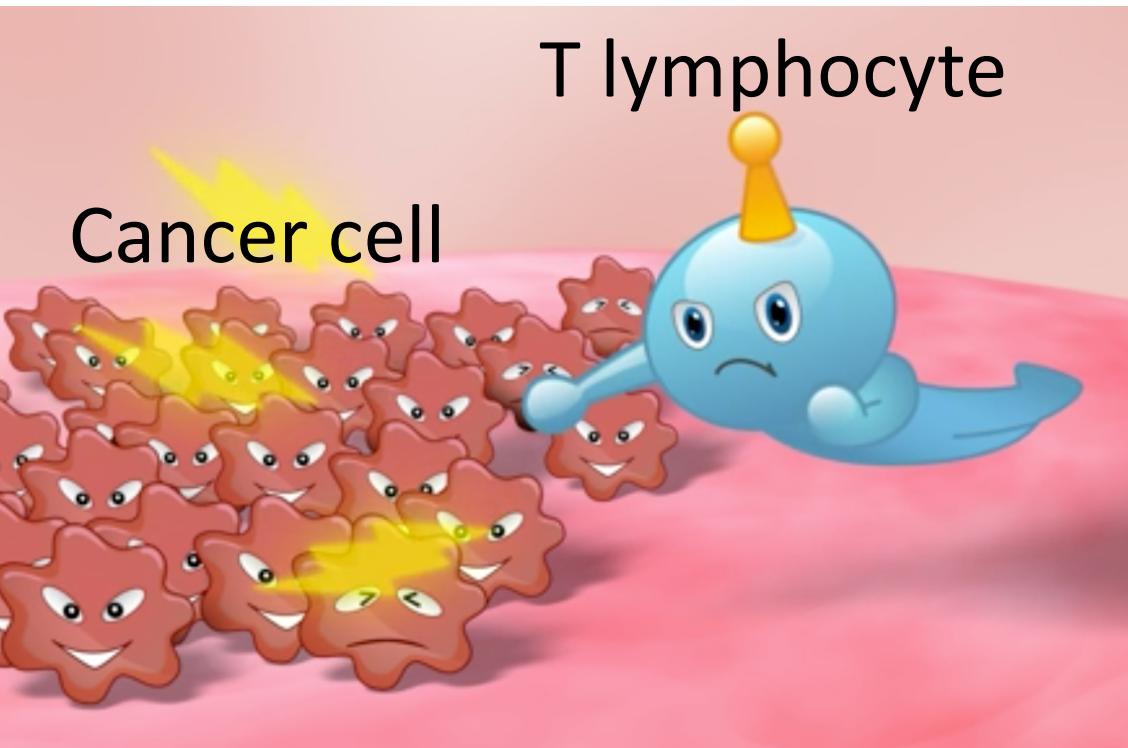
Bioinformatics Training and Education Program



# Is my result supported by other datasets?



# Tumor Immune Evasion



# Knowledge database

- Focused Presentation
  - [iATLAS](#) (Thorsson et al., Immunity 2018)
  - [TCIA](#) (Charoentong et al., Cell Report 2017)
- Customized Analysis
  - [TIDE](#) (Jiang et al., Nature Medicine 2018)
  - [TISIDB](#) (Ru et al., Bioinformatics 2019)

# iATLAS: Flagship website of TCGA

Study the immune ecosystem from bulk tumor profiles

CRI iAtlas Portal

[iAtlas Explorer Home](#)

[Analysis Modules](#)

- [Sample Group Overview](#)
- [Tumor Microenvironment](#)
- [Immune Feature Trends](#)
- [Clinical Outcomes](#)
- [Immunomodulators](#)
- [IO Targets](#)
- [TIL Maps](#)
- [Driver Associations](#)
- [CNV Associations](#)
- [Extracellular Networks](#)
- [Cell-Interaction Diagram](#)

[Data Description](#)

[Explorer Settings](#)

Divide samples by TCGA tumor type (TCGA Study), TCGA molecular subtypes (TCGA Subtype), or by immune subtypes that span multiple tumor types (Immune Subtype). Custom Sample Groups can also be uploaded, via the Sample Groups Overview module.

[Select Sample Groups](#)

[Explore](#) [Tools](#) [About](#) [Documentation](#) [Resources](#)

## iAtlas Explorer – Home

Select a module to explore CRI iAtlas data through interactive visualizations. You can organize the data by choosing how to divide tumor samples using "Select Sample Groups" on the left navigation bar. You can also select "Data Description" on the left navigation bar to learn which immune readouts are available.

### What's Inside

Immune Readouts: 86 Classes of Readouts: 12 TCGA Cancers: 33 TCGA Samples: 11,080

### Analysis Modules

Each module presents information organized by theme, with multiple views and interactive controls. Within each module, you can find "Manuscript Context" describing how that module can generate figures analogous to those in the manuscript *Thorsson et al., The Immune Landscape of Cancer, Immunity (2018)*.

#### Sample Group Overview

This module provides short summaries of your selected groups, and allows you to see how they overlap with other groups.

[Open Module](#)

#### Tumor Microenvironment

Explore the immune cell proportions in your sample groups.

[Open Module](#)

#### Immune Feature Trends

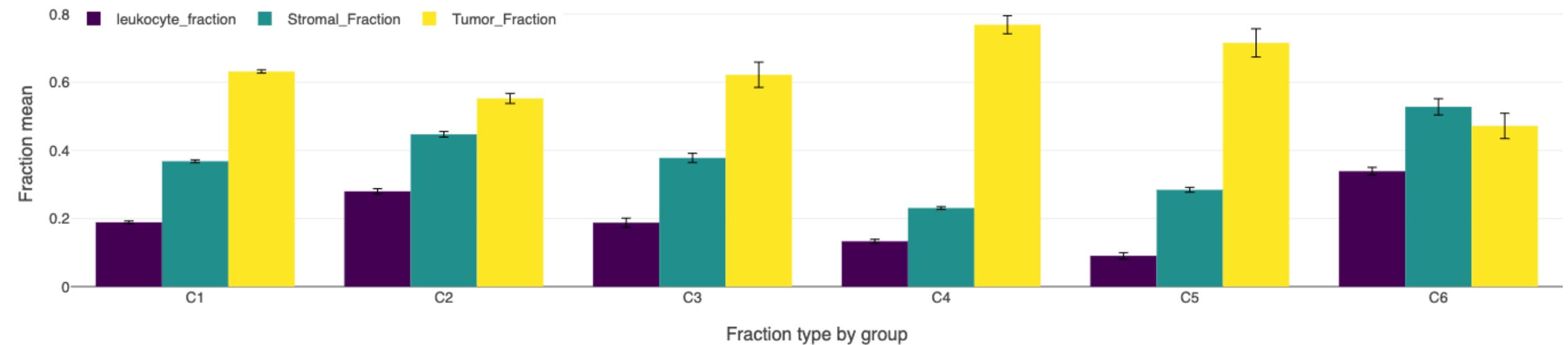
This module allows you to see how immune readouts vary across your groups, and how they relate to one another.

#### Clinical Outcomes

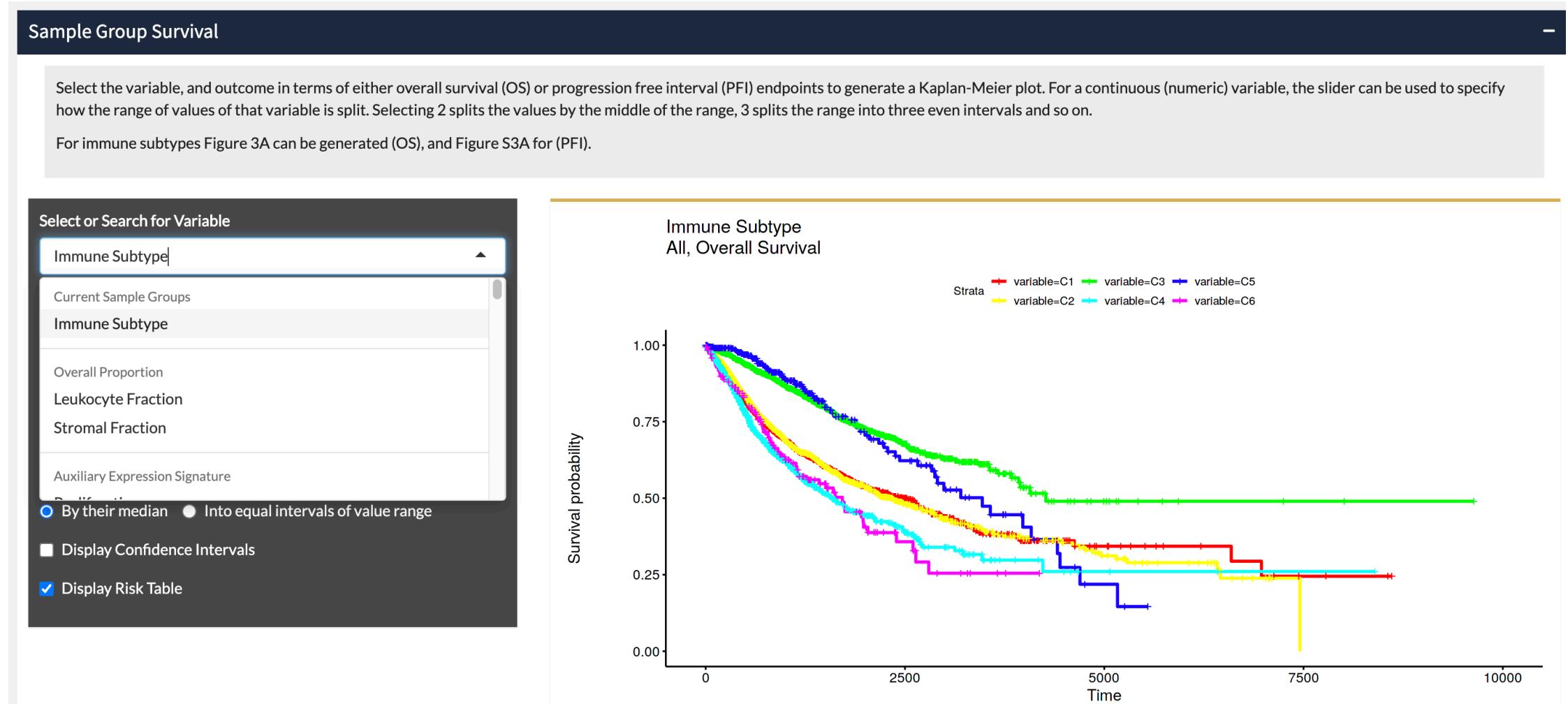
Plot survival curves based on immune characteristics and identify variables associated with outcome.

# iATLAS: Flagship website of TCGA

Major result to browser, the six clusters they defined



# Select subtypes to browse TCGA association



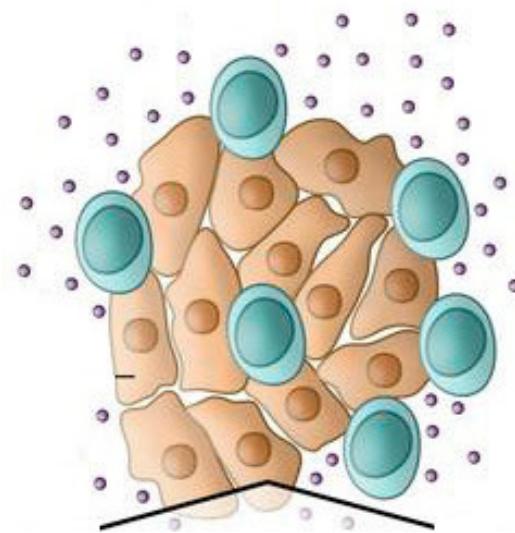
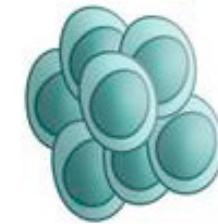
# Knowledge database

- Focused Presentation
  - iATLAS (Thorsson et al., Immunity 2018)
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- Customized Analysis
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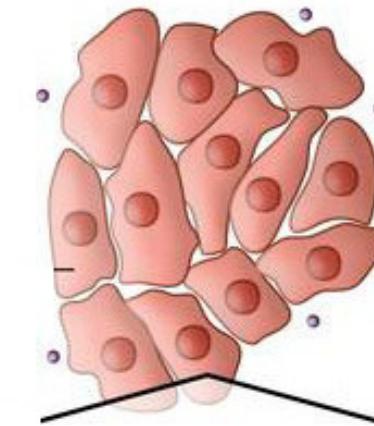
# TIDE: Tumor Immune Dysfunction and Exclusion

<http://tide.dfci.harvard.edu>

Cytotoxic T Lymphocyte



T cell Dysfunction  
CTL high tumor

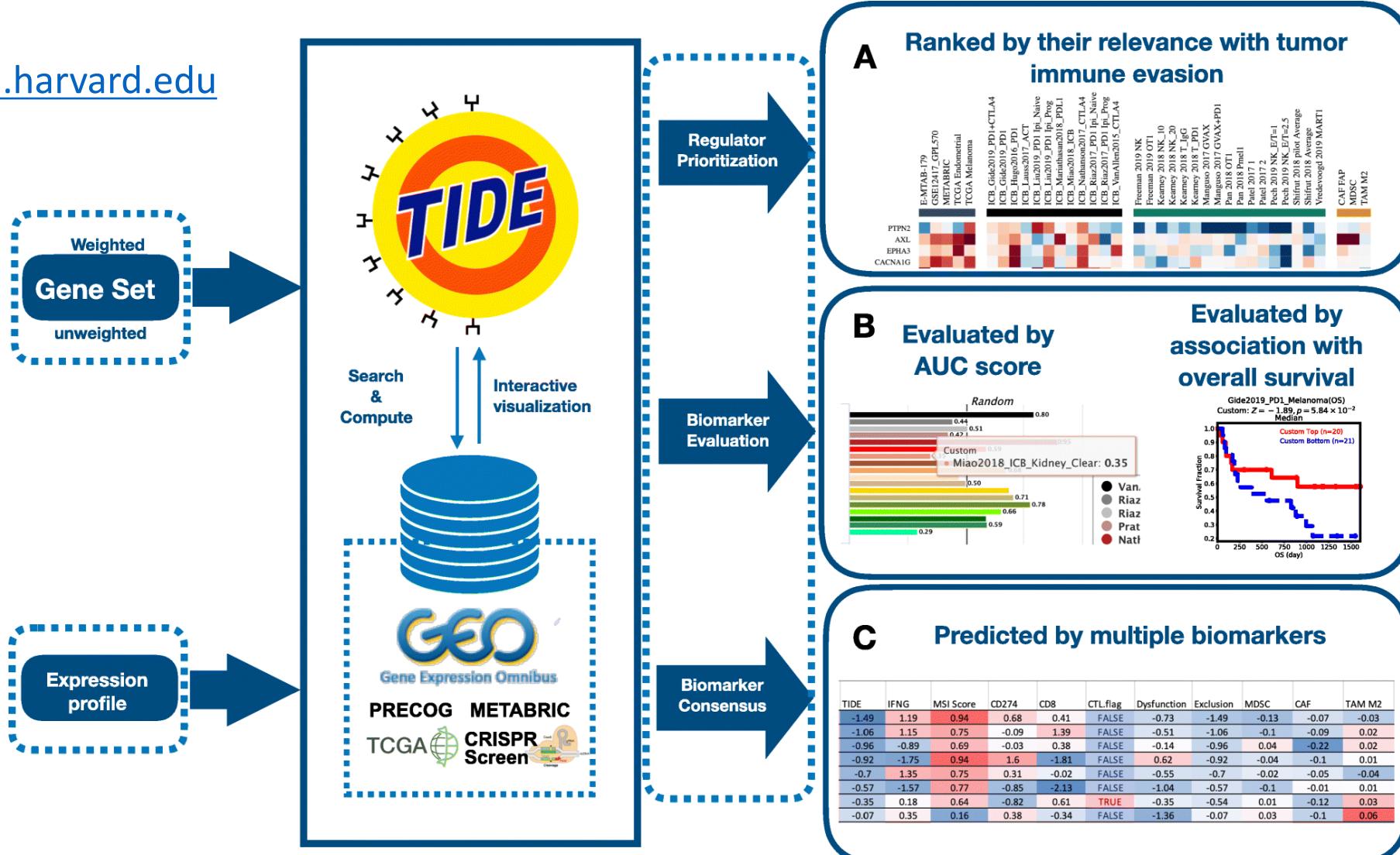


T cell Exclusion  
CTL low tumor

(Gajewski, Schreiber, Fu et al., 2013)

# TIDE: Tumor Immune Dysfunction and Exclusion

<http://tide.dfci.harvard.edu>

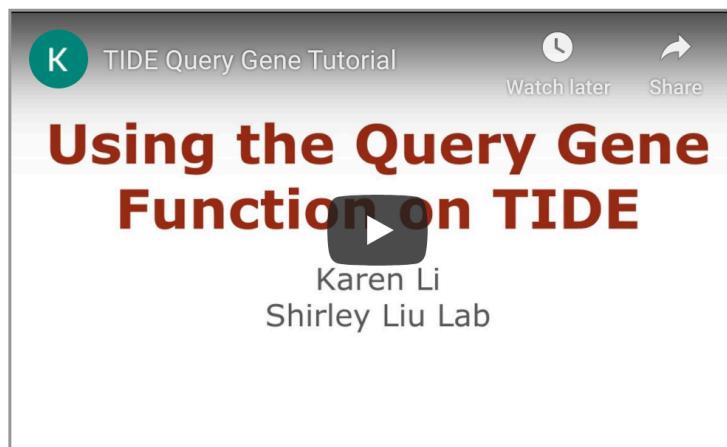


# Gene Query

## TIDE: Tumor Immune Dysfunction and Exclusion

TIDE also provides data-driven gene signatures of T-cell dysfunction and immunotherapy resistance, computed from a large amount of cancer clinical datasets.

[Tutorial video of gene query](#)



[Download the video](#)

Type a gene name. (e.g., "PDL1" or "SERPINB9").

[Search](#)

# Gene Query: Example TGFB1

## Result for query: TGFB1 (7040)

We listed the high confidence results (Core) and full range results (Expression, Copy\_Number, etc.) from TIDE analysis. We also included several reference results, including Ref\_Therapy and Ref\_Screen, to show the gene level scores in immunotherapy clinical response and CRISPR screen of anticancer immunity. Please click each tab for individual section.

Core Expression Copy\_Number Methylation Exclusion Ref\_Therapy Ref\_Screen

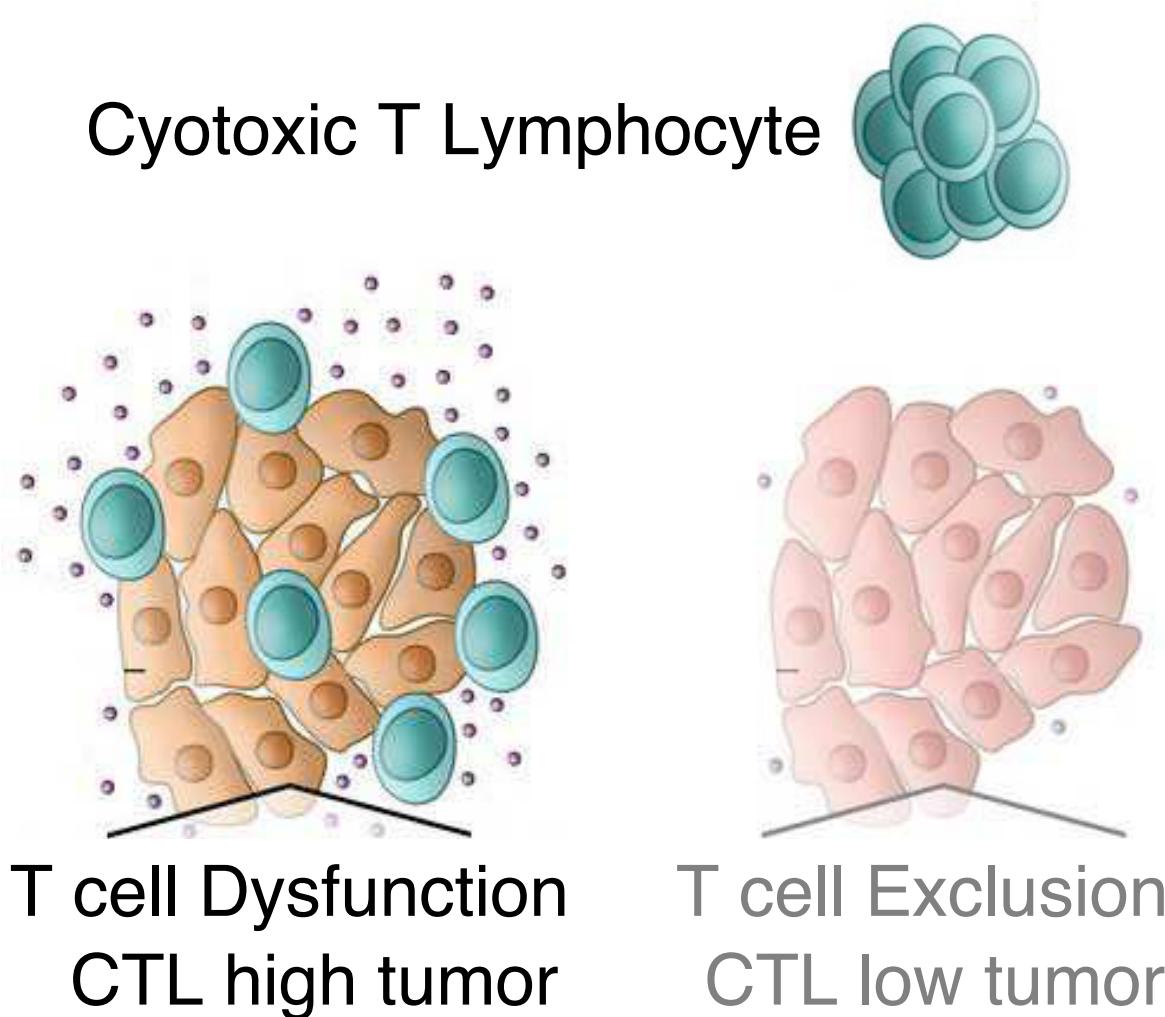
Most confident results using gene expression data

Click table header for sorting. Hover your mouse on a cell for description or full name of abbreviation.

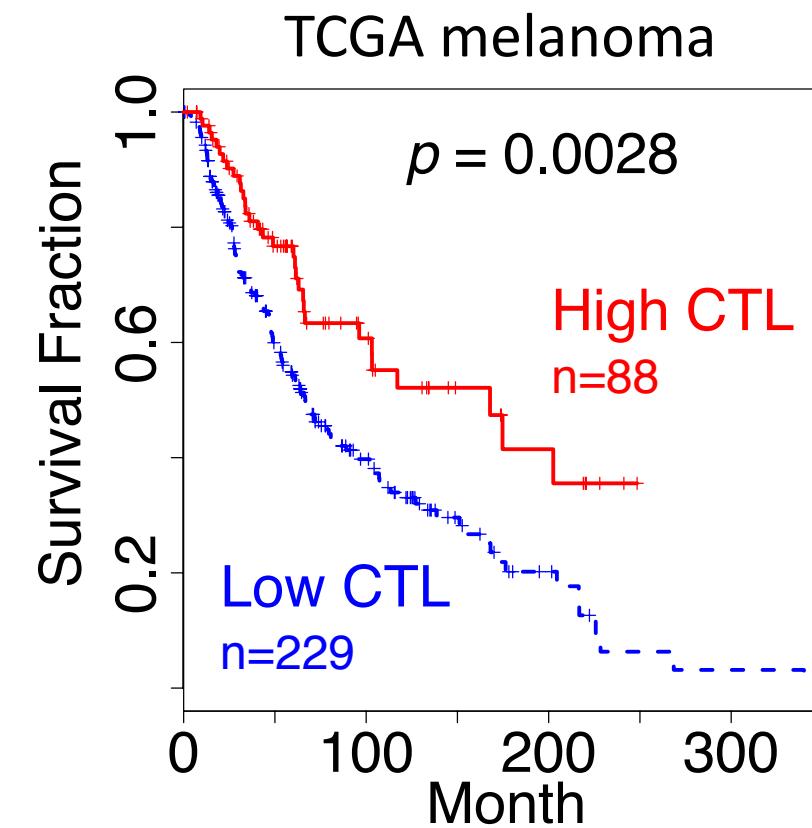
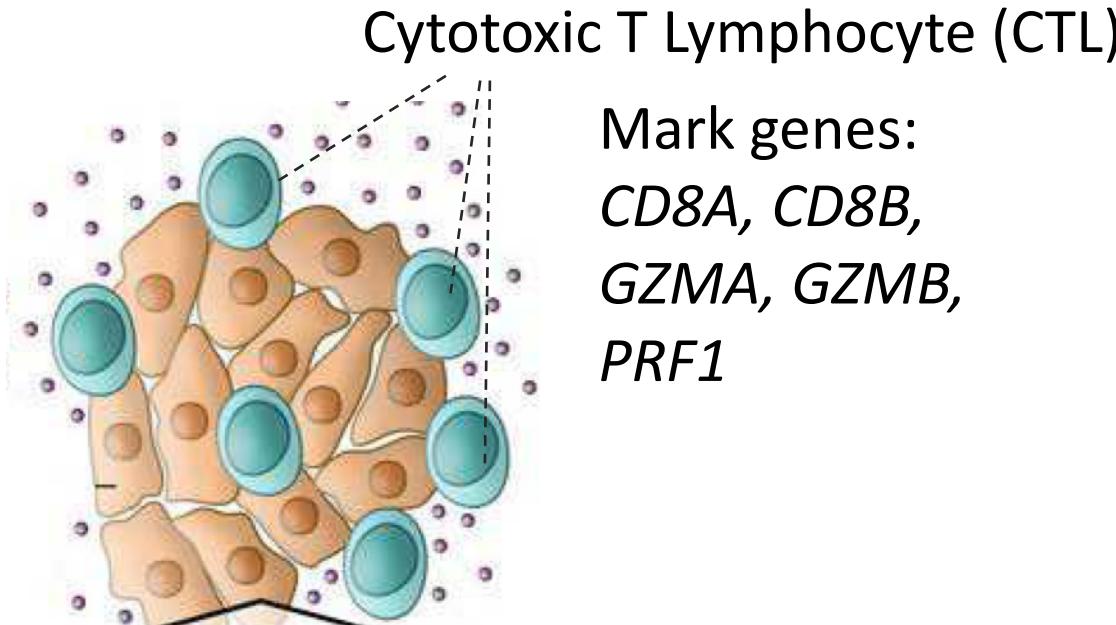
♦ Cohort	♦ Cancer	♦ Subtype	♦ CTL Cor	♦ T Dysfunction	♦ Risk	♦ Risk.adj	♦ Count
TCGA	Melanoma	Metastatic	0.385 	3.471 	-1.424 	-0.519	317
TCGA	Endometrial		0.296 	3.02 	-0.167 	0.015	541
METABRIC	Breast	TN	0.079 	1.268 	0.766 	0.891	233
GSE12417_GPL570	Leukemia	AML	0.013 	0.265 	0.877 	0.511	79
E-MTAB-179	Brain	Neuroblastoma	0.49 	0.158 	-0.37 	0.774	389

Export to CSV

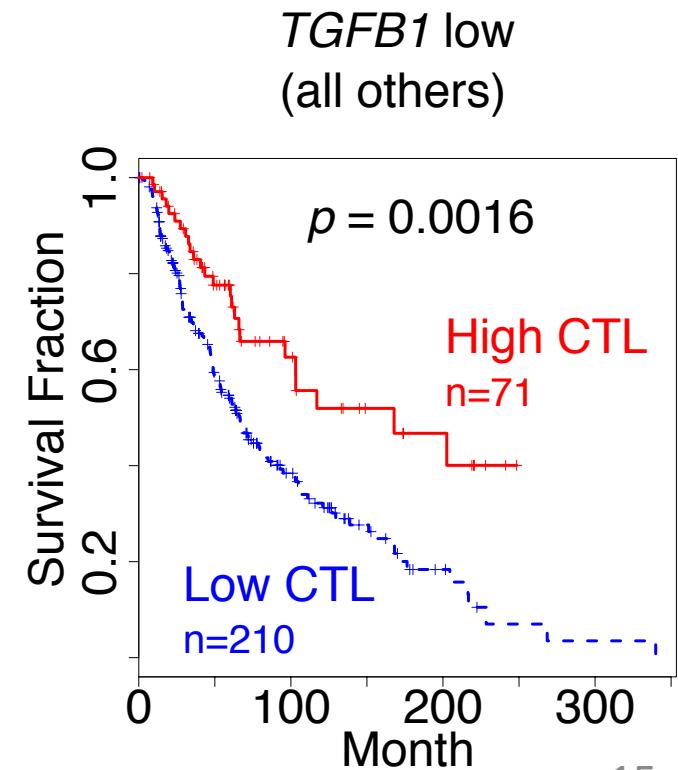
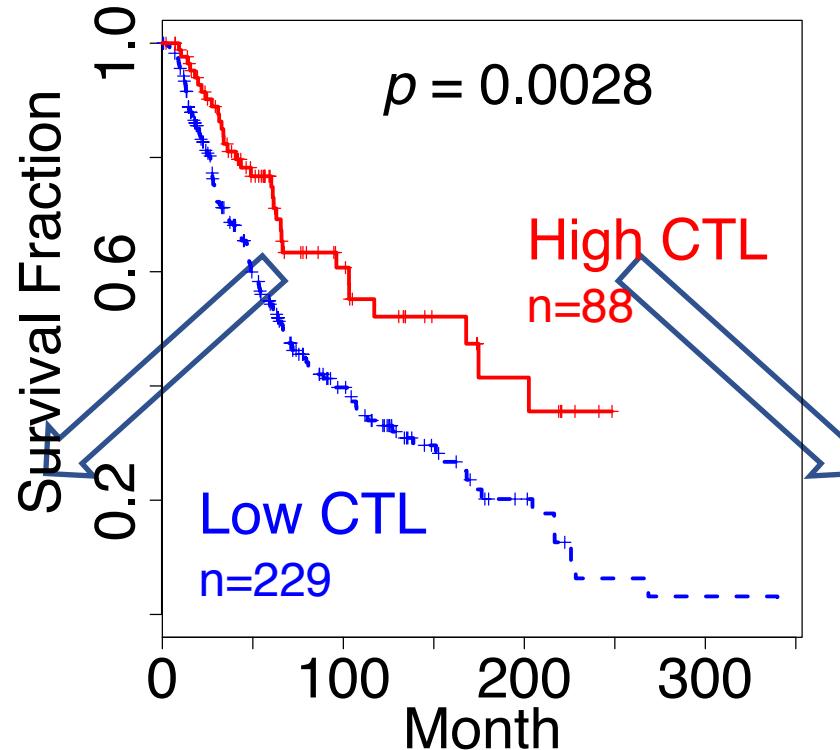
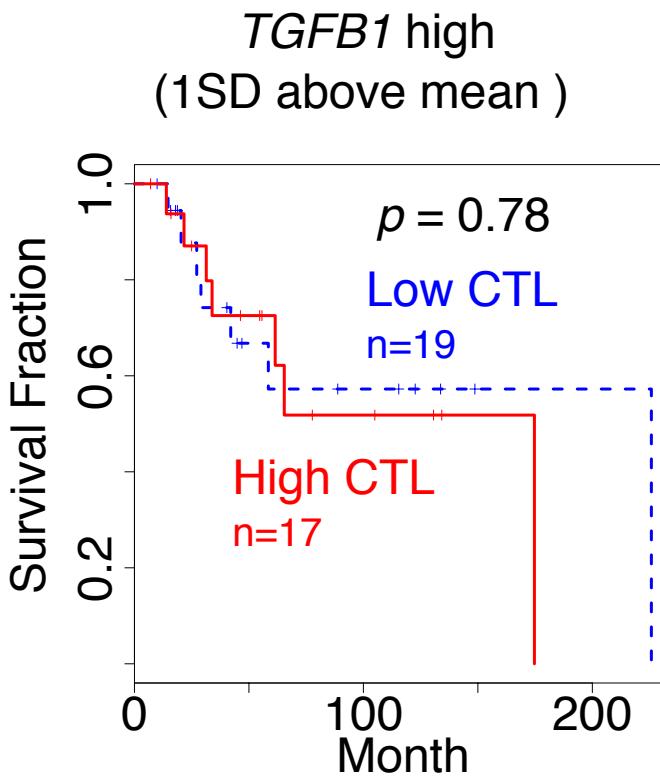
# T-cell Dysfunction in CTL-high Tumors



# High level of cytotoxic T lymphocyte indicates better survival



# Association between CTL and survival depends on *TGFB1* level



# T-cell dysfunction test in a linear model

Death Hazard



*TGFB1* expression

CTL (Cytotoxic T Lymphocyte)

$$\text{Hazard} = a * \text{CTL} + b * P + \underline{d * \text{CTL} * P}$$

$$\text{T cell dysfunction score} = d / \text{StdErr}(d)$$

# Antagonistic Interaction between CTL and *TGFB1*

	Coef	Stderr	Z	Pr(> z )
Age	0.02	0.01	3.55	3.78E-04
Gender	0.02	0.17	0.12	9.07E-01
Stage	0.29	0.09	3.31	9.34E-04
CTL	-0.50	0.15	-3.32	9.05E-04
<i>TGFB1</i>	-0.10	0.10	-1.04	3.00E-01
<i>CTL * TGFB1</i>	0.11	0.03	3.47	5.18E-04

Hazard = c1\*Age + c2\*Gender + c3\*Stage + a\*CTL + b\*TGFB1 + d\* CTL \* TGFB1

Background

Interaction

# Interaction between variables matters!

*TGFB1* encodes an immuno-suppressive cytokine (Sharma et al., 2017)

	Coef	StdErr	Z-score	Pr(> z )
Age	0.02	0.01	3.95	7.85E-05
Gender	0.00	0.17	0.00	9.97E-01
Stage	0.30	0.09	3.36	7.74E-04
<i>TGFB1</i>	-0.13	0.09	-1.42	1.55E-01

*TGFB1* alone associate with lower death risk

Correlation(*TGFB1*, CTL) = 0.39

	Coef	StdErr	Z-score	Pr(> z )
Age	0.02	0.01	3.55	3.79E-04
Gender	0.02	0.17	0.12	9.08E-01
Stage	0.29	0.09	3.31	9.34E-04
CTL	-0.54	0.17	-3.29	9.95E-04
<i>TGFB1</i>	-0.10	0.10	-0.97	3.31E-01
<i>CTL*TGFB1</i>	0.13	0.04	3.47	5.28E-04

*TGFB1* antagonizes the effect of cytotoxic T lymphocyte

# Synergistic Interaction between CTL and *SOX10*

	Coef	Stderr	Z	Pr(> z )
Age	0.02	0.01	3.26	1.11E-03
Gender	0.03	0.17	0.15	8.80E-01
Stage	0.29	0.09	3.33	8.63E-04
CTL	-0.79	0.21	-3.79	1.51E-04
<i>SOX10</i>	-0.01	0.10	-0.11	9.10E-01
<i>CTL * SOX10</i>	-0.59	0.16	-3.69	2.23E-04

$$\text{Hazard} = c_1 * \text{Age} + c_2 * \text{Gender} + c_3 * \text{Stage} + a * \text{CTL} + b * \text{SOX10} + d * \text{CTL} * \text{SOX10}$$

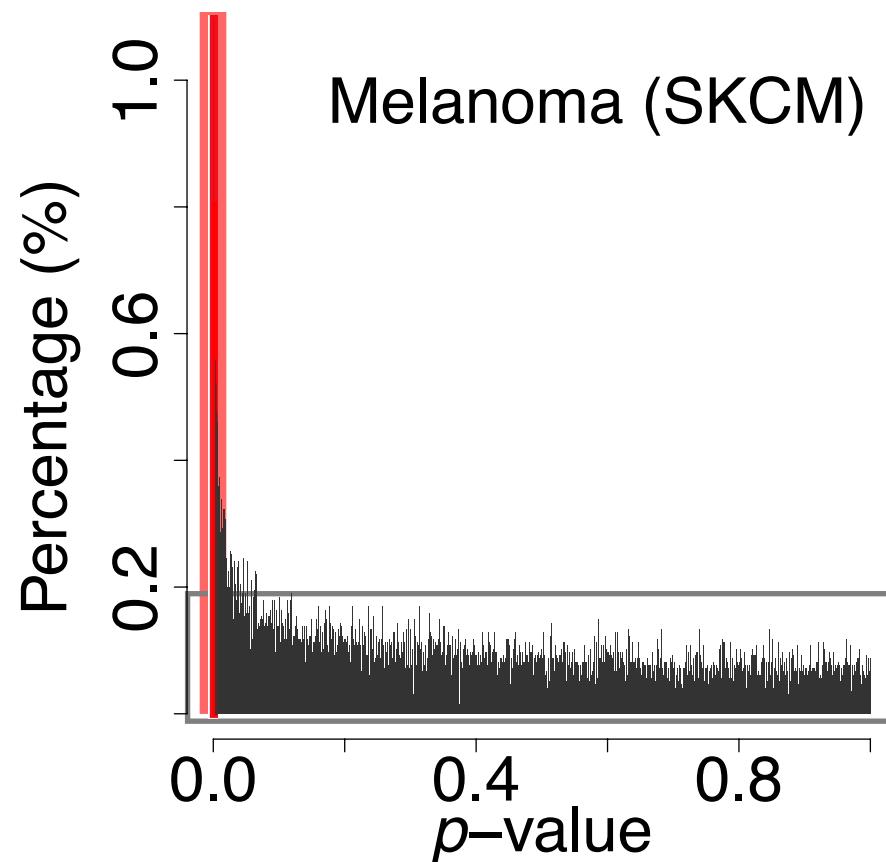
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Background

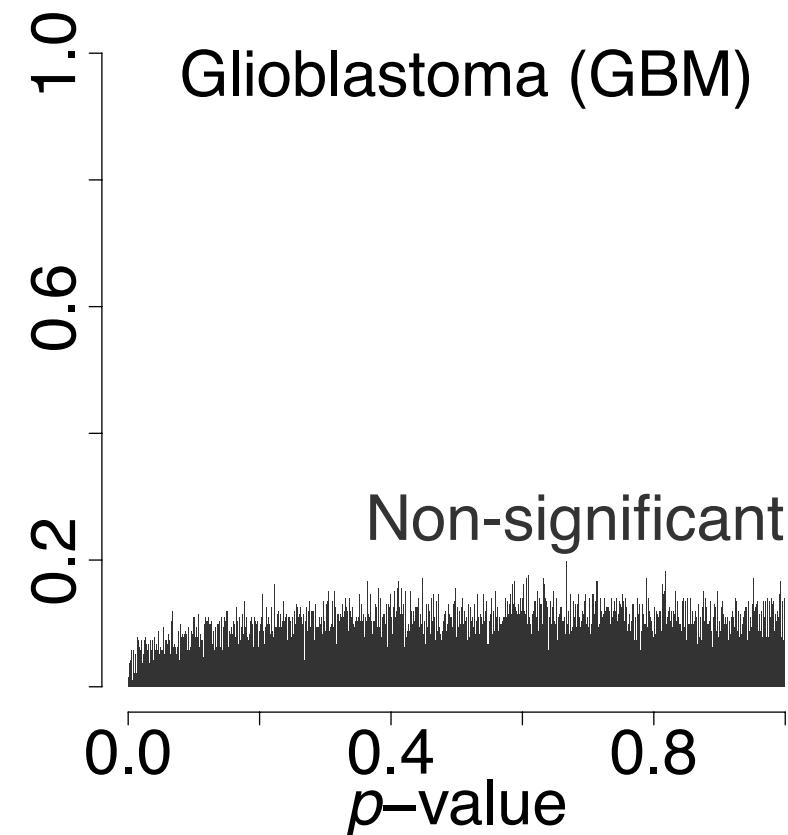
Interaction

*SOX10* level in cancer cells can promote the T-cell mediated tumor killing  
(Patel et al., 2017; Khong et al., 2002).

The  $p$ -value histogram should have a significant peak



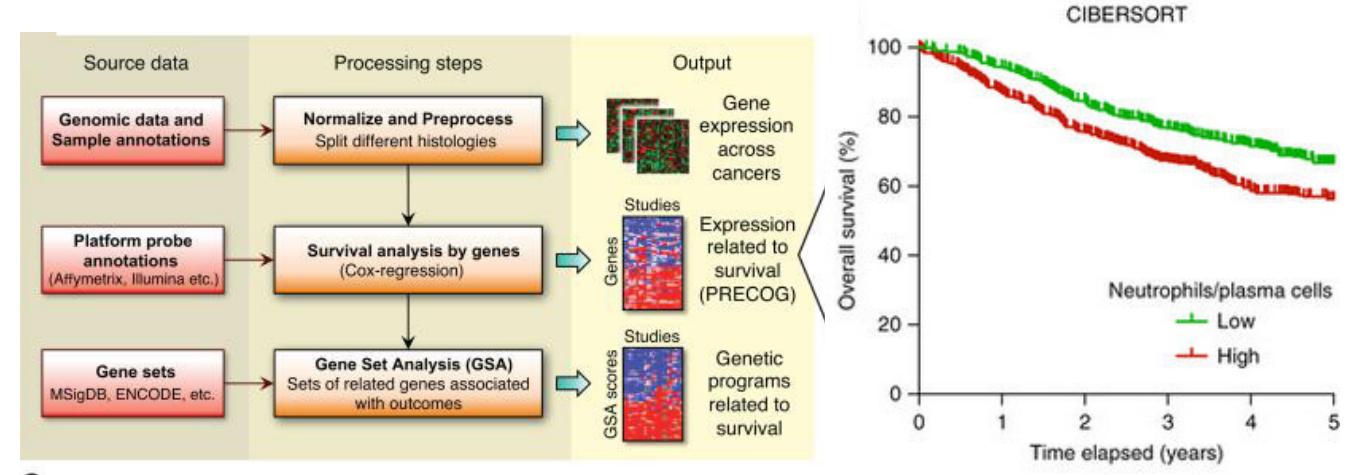
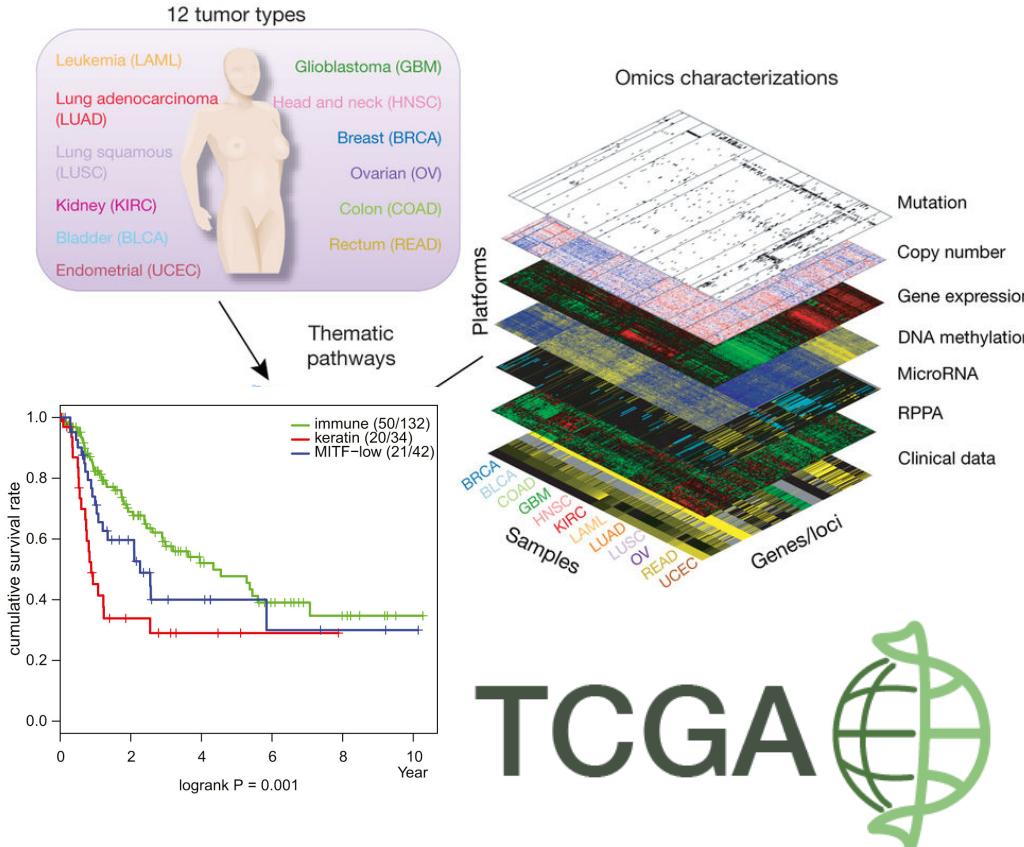
Melanoma (SKCM)



Glioblastoma (GBM)

Non-significant

# Large-scale Cancer Genomics Data Cohorts



PRECOG 135 cohorts 18K samples

NATURE | ARTICLE

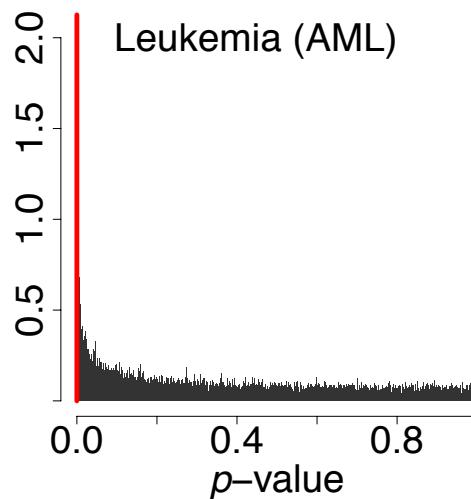
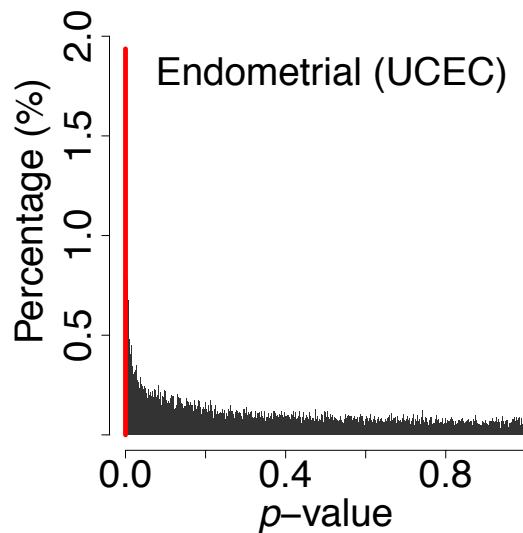
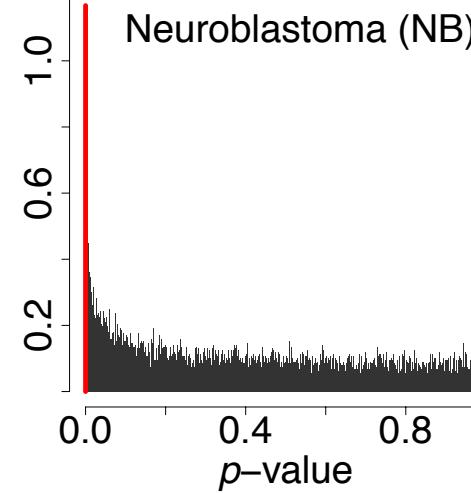
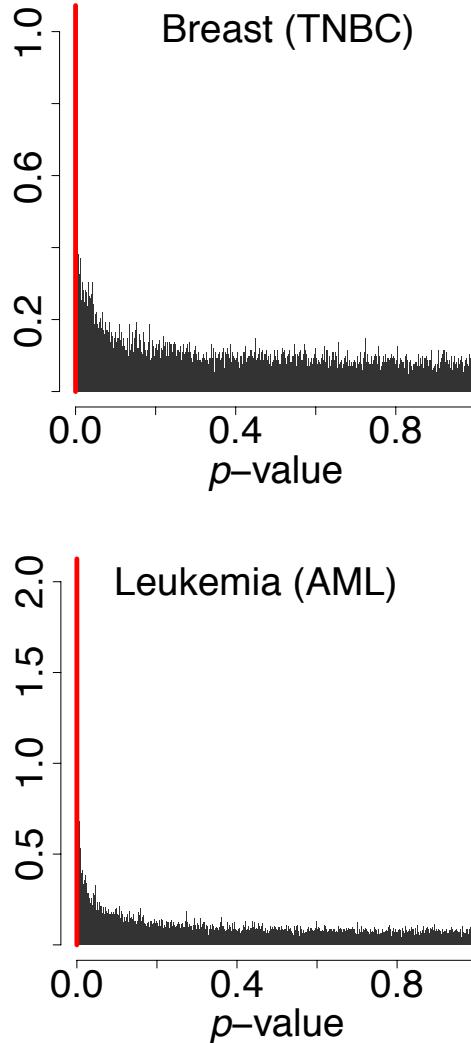
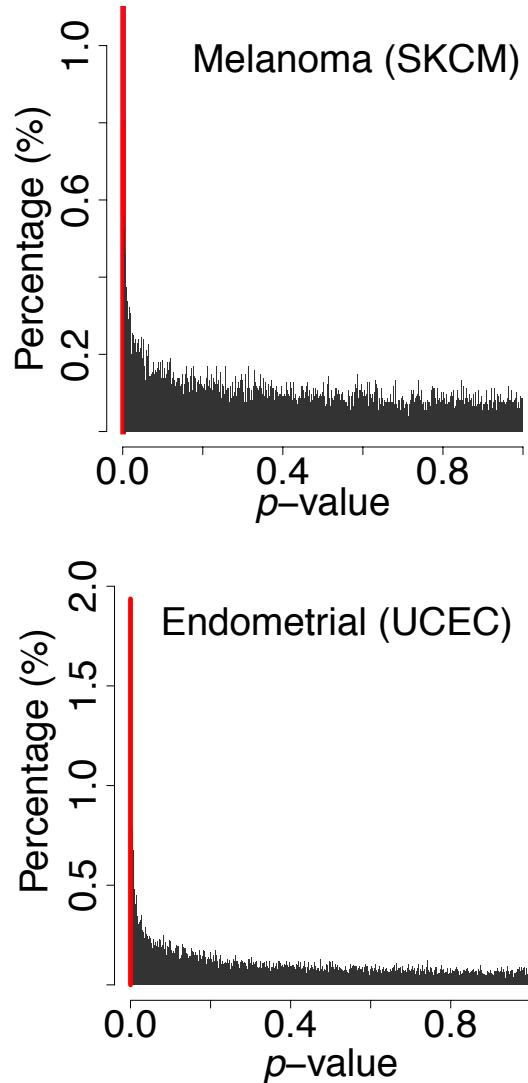
日本語要約

The genomic and transcriptomic architecture of 2,000 breast tumours reveals novel subgroups

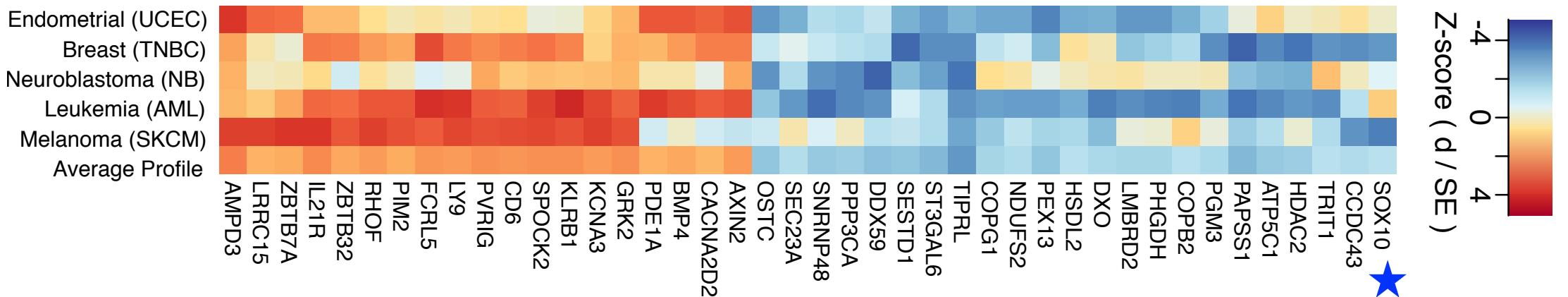
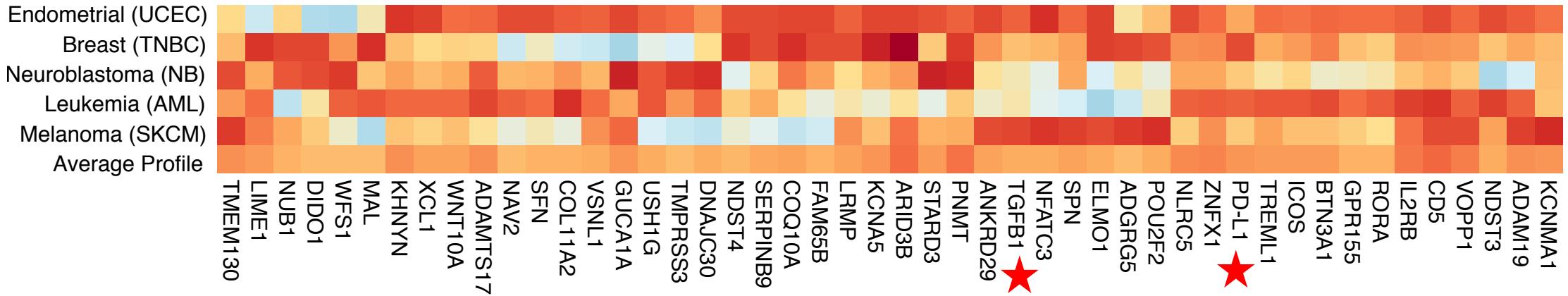
Christina Curtis, Sohrab P. Shah, Suet-Feung Chin, Gulisa Turashvili, Oscar M. Rueda, Mark J. Dunning, Doug Speed, Andy G. Lynch, Shamith Samarajiwa, Yinyin Yuan, Stefan Gräf, Gavin Ha, Gholamreza Haffari, Ali Bashashati, Roslin Russell, Steven McKinney, METABRIC Group, Anita Langerød, Andrew Green, Elena Provenzano, Gordon Wishart, Sarah Pinder, Peter Watson, Florian Markowetz, Leigh Murphy + et al.

METABRIC

# Five datasets with significant $p$ -value peaks



# Genes with Significant T Dysfunction Scores



# Correlation with Cytotoxic T Lymphocyte Level

Result for query: TGFB1 (7040) 

We listed the high confidence results (Core) and full range results (Expression, Copy\_Number, etc.) from T' scores in immunotherapy clinical response and CRISPR screen of anticancer immunity. Please click each

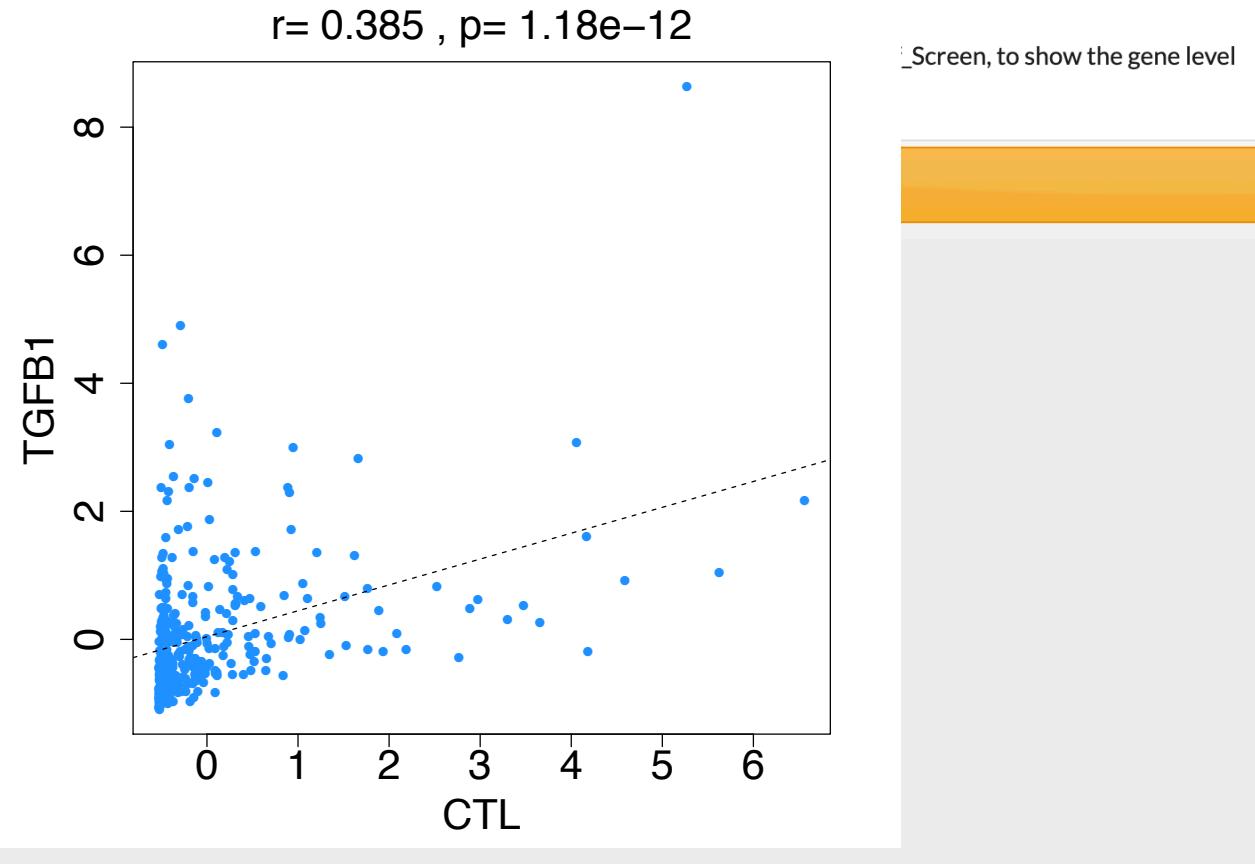
Core Expression Copy\_Number Methylation Exclusion Ref.

Most confident results using gene expression data

Click table header for sorting. Hover your mouse on a cell for description or

Cohort	Cancer	Subtype	CTL Cor	
TCGA	Melanoma	Metastatic	0.385 	
TCGA	Endometrial		0.296 	3.02 
METABRIC	Breast	TN	0.079 	1.268 
GSE12417_GPL570	Leukemia	AML	0.013 	0.265 
E-MTAB-179	Brain	Neuroblastoma	0.49 	0.158 

Export to CSV



# Correlation with Death Risk

## Result for query: TGFB1 (7040)

We listed the high confidence results (Core) and full range results (Expression, Copy\_Number, etc.) from TIDE analysis. We also included scores in immunotherapy clinical response and CRISPR screen of anticancer immunity. Please click each tab for individual section.

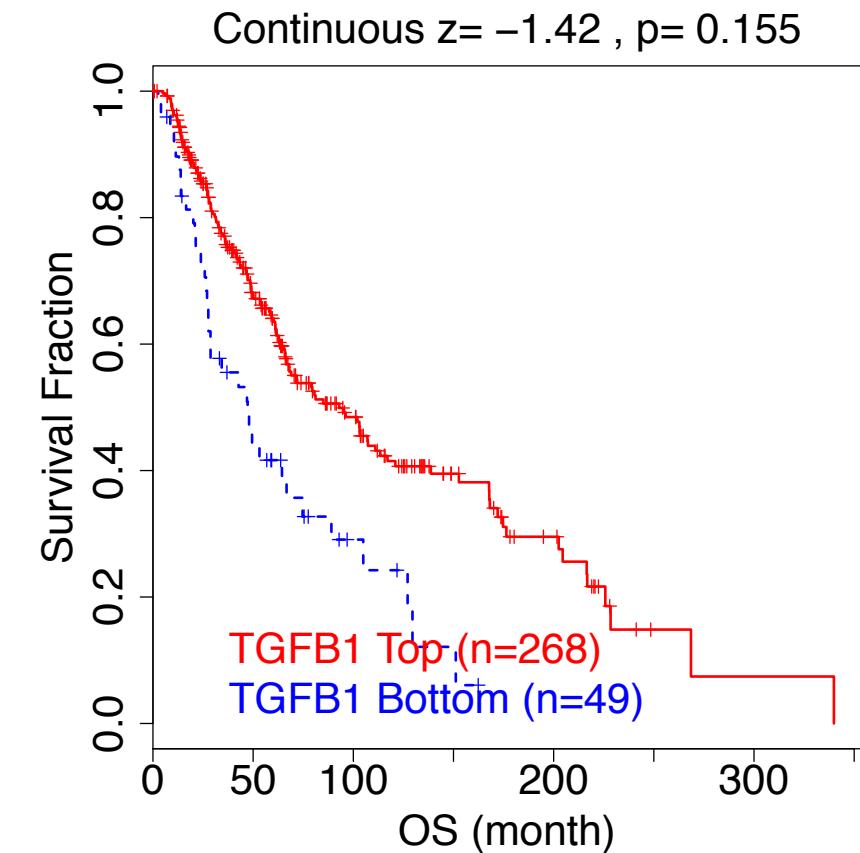
Core Expression Copy\_Number Methylation Exclusion Ref\_Therapy Ref\_Screen

Most confident results using gene expression data

Click table header for sorting. Hover your mouse on a cell for description or full name of abbreviation.

Cohort	Cancer	Subtype	CTL Cor	T Dysfunction	Risk
TCGA	Melanoma	Metastatic	0.385 	3.471 	-1.424 
TCGA	Endometrial		0.296 	3.02 	-0.167 
METABRIC	Breast	TN	0.079 	1.268 	0.766 
GSE12417_GPL570	Leukemia	AML	0.013 	0.265 	0.877 
E-MTAB-179	Brain	Neuroblastoma	0.49 	0.158 	-0.37 

Export to CSV



# Association with T cell Dysfunction : Core

Result for query: TGFB1 (7040) 

We listed the high confidence results (Core) and full range results (Expression, Copy\_Number, etc.) from TIDE analysis scores in immunotherapy clinical response and CRISPR screen of anticancer immunity. Please click each tab for more details.

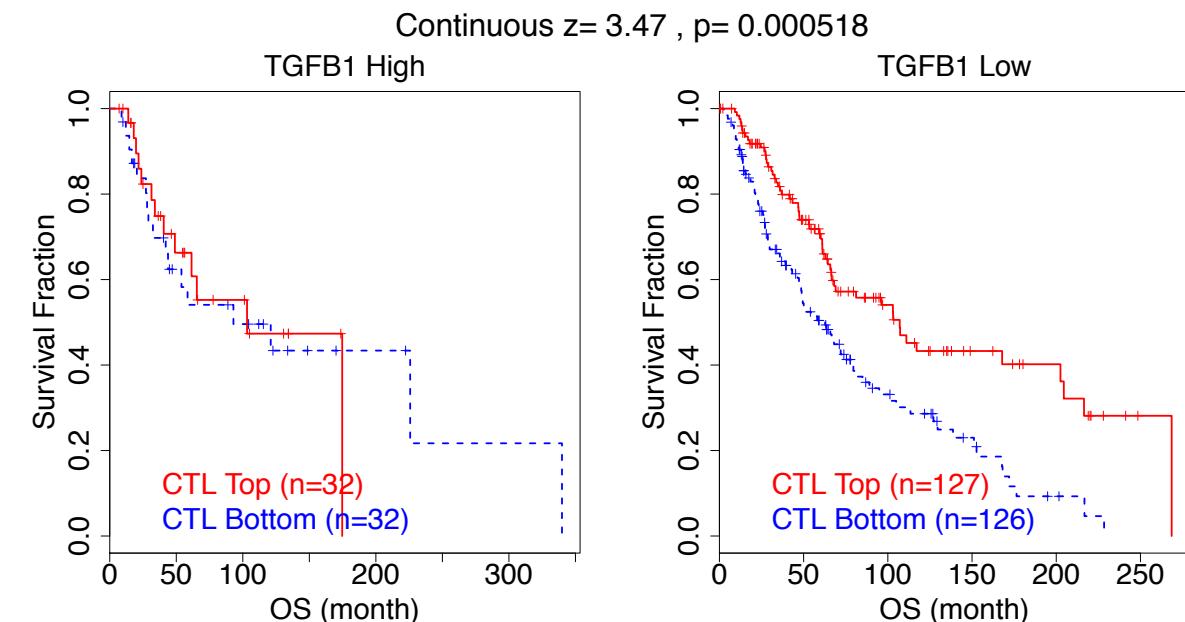
Core Expression Copy\_Number Methylation Exclusion Ref\_Therapy

Most confident results using gene expression data

Click table header for sorting. Hover your mouse on a cell for description or full name of analysis.

Cohort	Cancer	Subtype	CTL Cor	T Dysfunct
TCGA	Melanoma	Metastatic	0.385 	3.471 
TCGA	Endometrial		0.296 	3.02 
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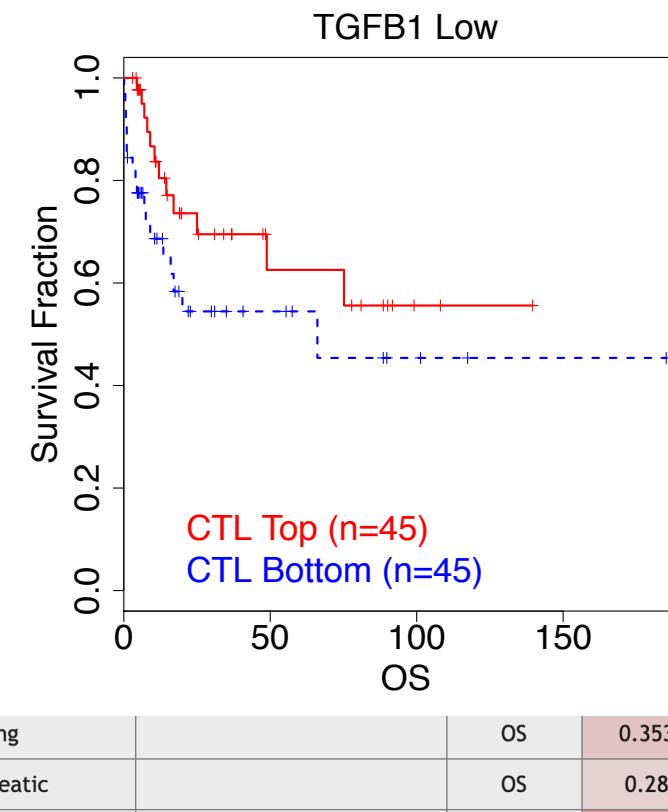
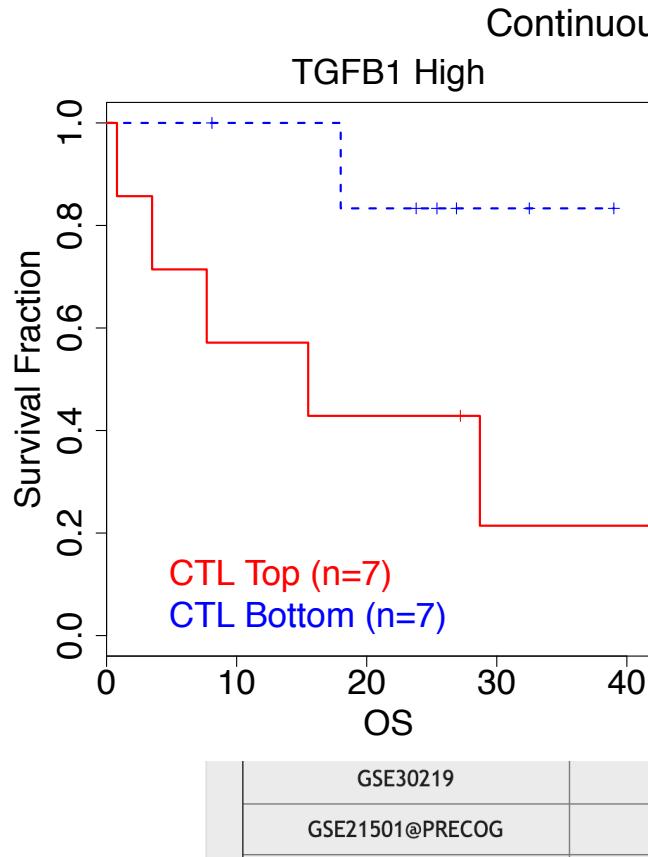
Export to CSV



# Association with T cell Dysfunction : More

Result for query: TGFB1 (7040) 

We listed the high confidence results (Core) and full range results (Expression, Copy\_Number, etc.) from TIDE analysis. We also included several reference results, including Ref\_Therapy and Ref\_Screen, to show the gene level scores in immunotherapy clinical response and CRISPR screen of anticancer immunity. Please click each tab for individual section.



# Exclusion : Example PTGS2

## Result for query: PTGS2 (5743)

We listed the high confidence results (Core) and full range results (Expression, Copy\_Number, etc.) from TIDE analysis. We also included several reference results, including Ref\_Therapy and Ref\_Screen, to show the gene level scores in immunotherapy clinical response and CRISPR screen of anticancer immunity. Please click each tab for individual section.

Core Expression Copy\_Number Methylation Exclusion Ref\_Therapy Ref\_Screen

The gene expression value in T cell exclusion signatures

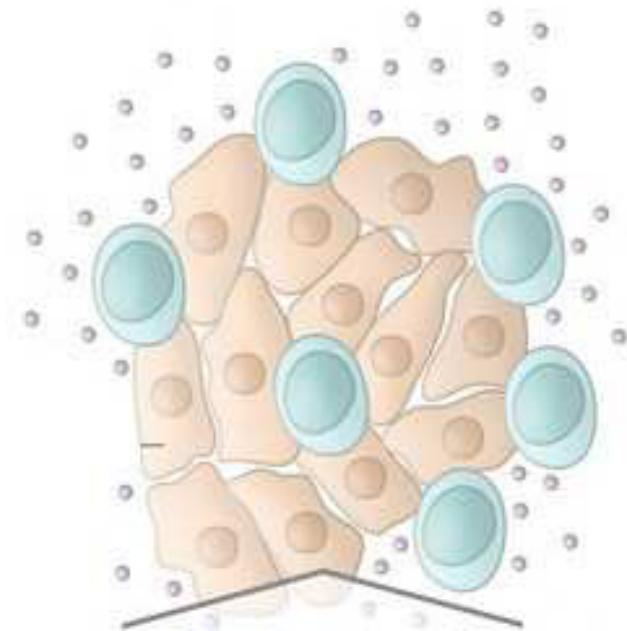
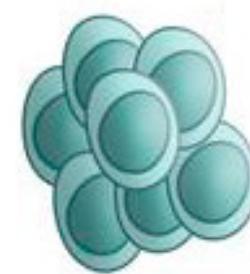
Click table header for sorting. Hover your mouse on a cell for description or full name of abbreviation.

Condition	Z-score
MDSC	3.424
CAF FAP	1.526
TAM M2	-5.725

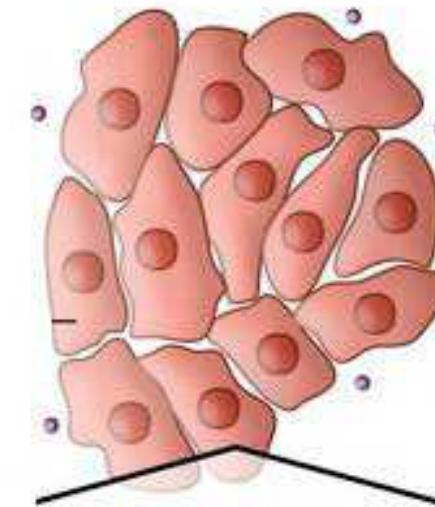
Export to CSV

# Tumor Immune Evasion through T-cell Exclusion

Cyotoxic T Lymphocyte



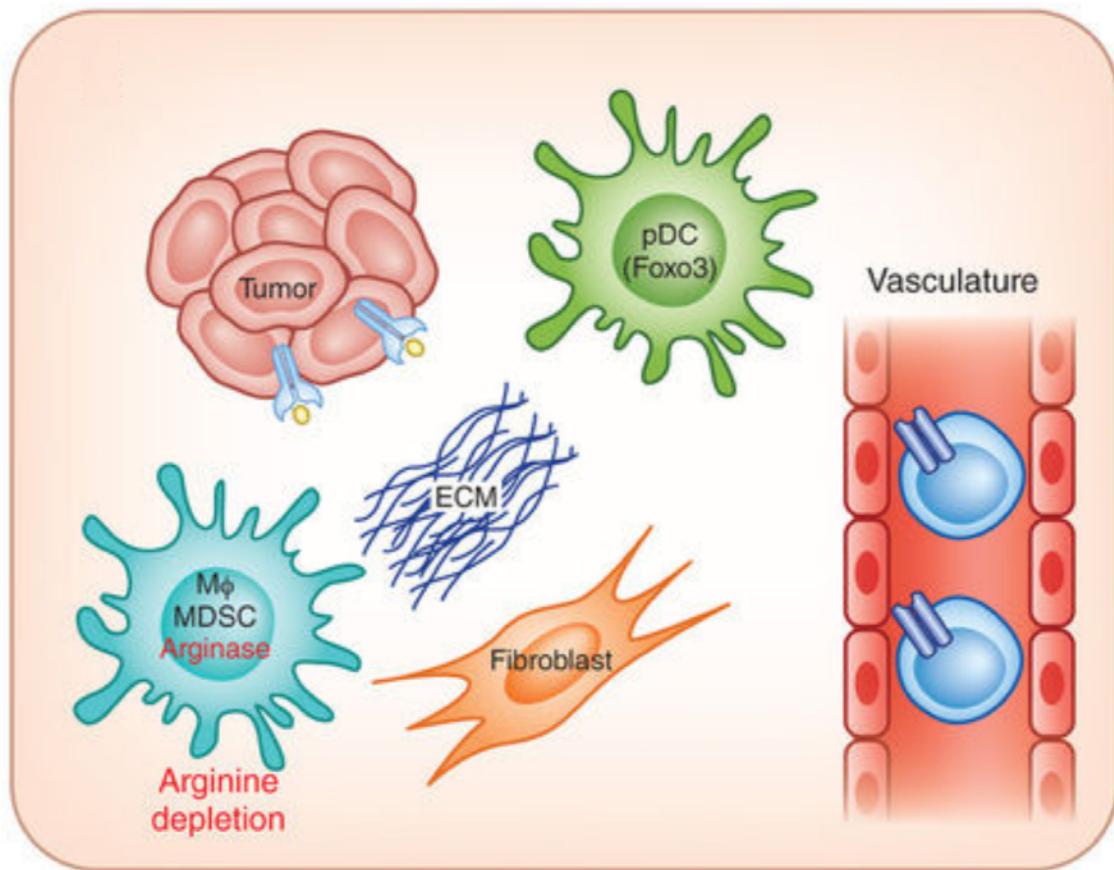
T cell Dysfunction  
CTL high tumor



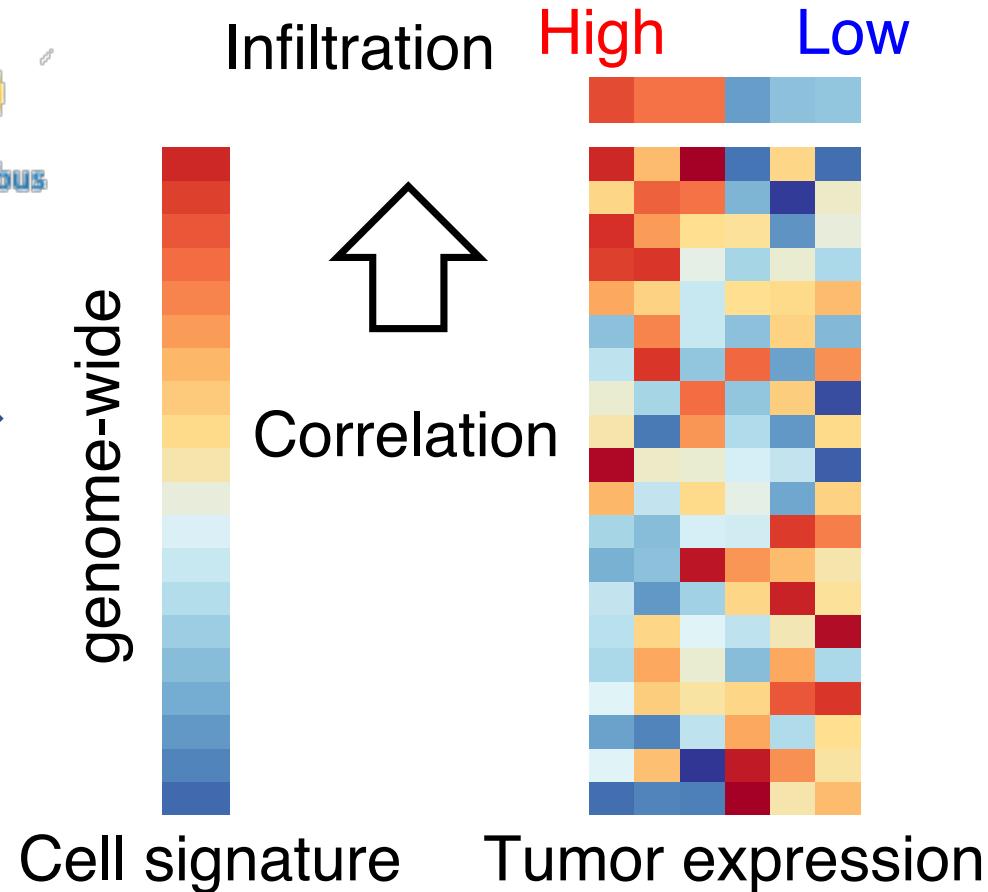
T cell Exclusion  
CTL low tumor

# Immunosuppressive Cell Types in T-cell Exclusion

## T cell exclusion factors

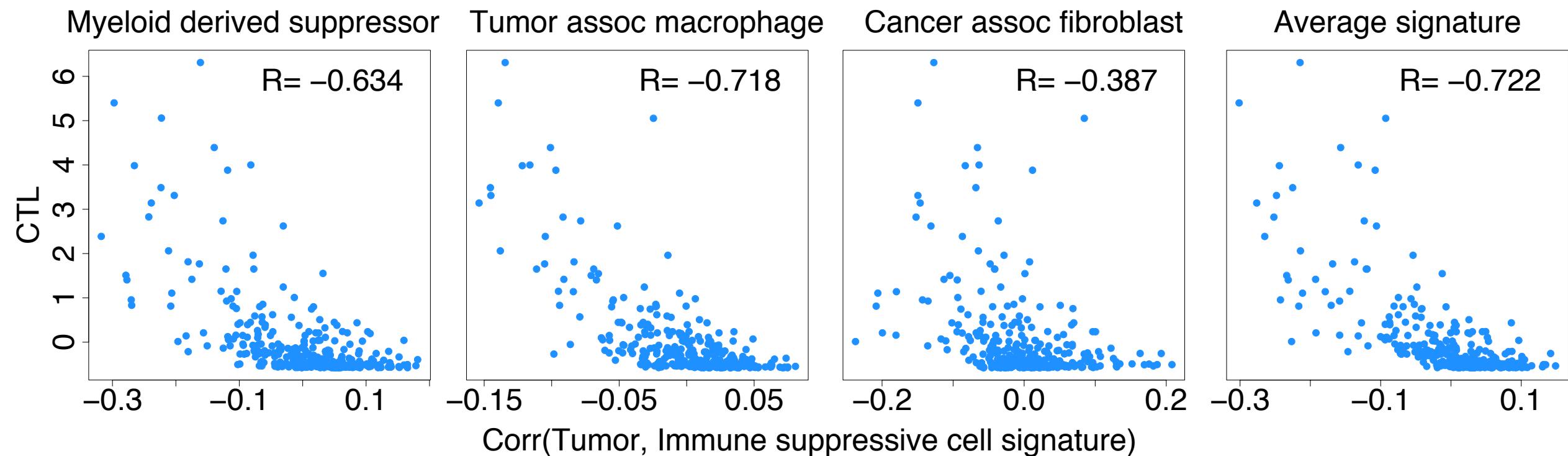


GEO  
Gene Expression Omnibus

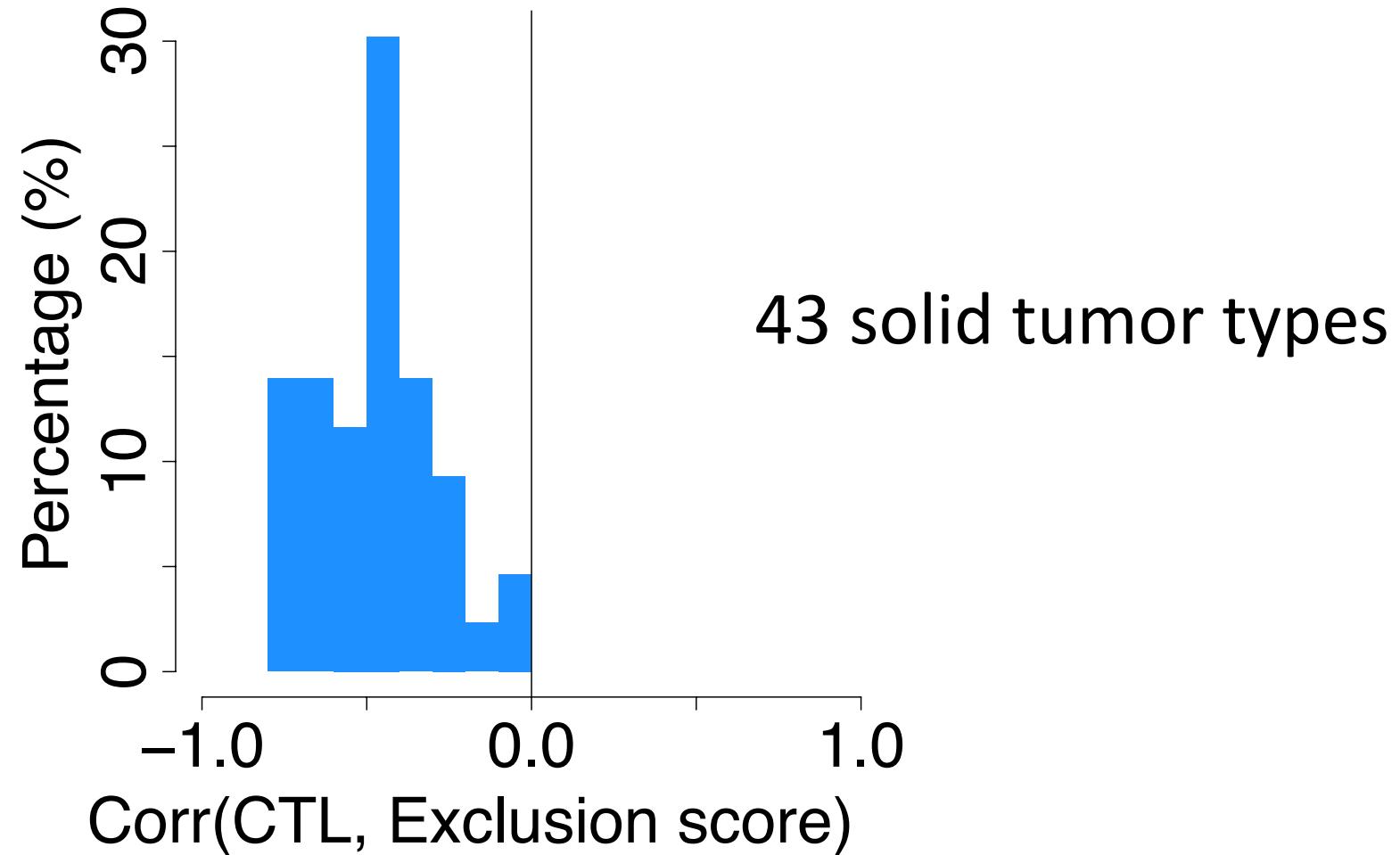


(Gajewski, Schreiber, Fu et al., 2013)  
(Dougan et al., 2017)

# Immunosuppressive cell signatures predict T-cell exclusion in tumors



# Immunosuppressive cell signatures predict T-cell exclusion in all solid tumors



# Exclusion : Example PTGS2

## Result for query: PTGS2 (5743)

We listed the high confidence results (Core) and full range results (Expression, Copy\_Number, etc.) from TIDE analysis. We also included several reference results, including Ref\_Therapy and Ref\_Screen, to show the gene level scores in immunotherapy clinical response and CRISPR screen of anticancer immunity. Please click each tab for individual section.

Core Expression Copy\_Number Methylation Exclusion Ref\_Therapy Ref\_Screen

The gene expression value in T cell exclusion signatures

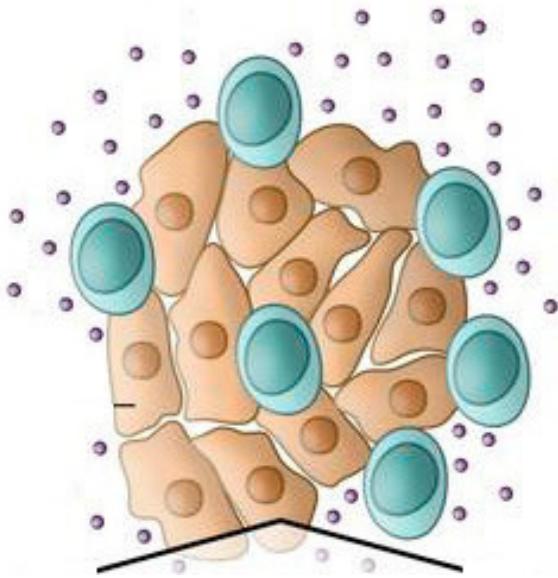
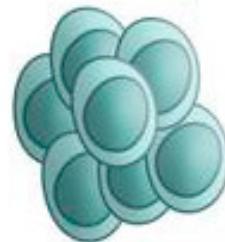
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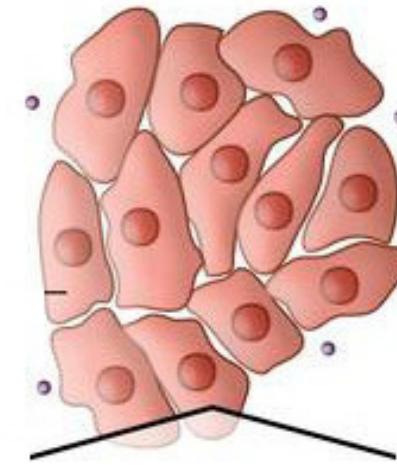
Export to CSV

# Two Categories of Tumor Immune Evasion

Cytotoxic T Lymphocyte



T cell Dysfunction  
CTL high tumor



T cell Exclusion  
CTL low tumor

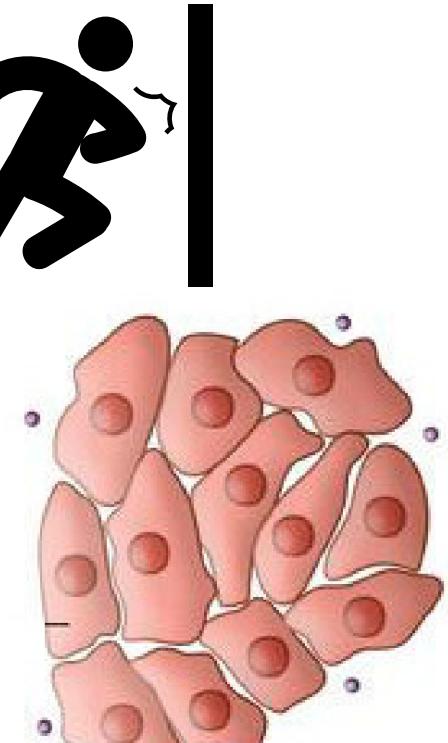
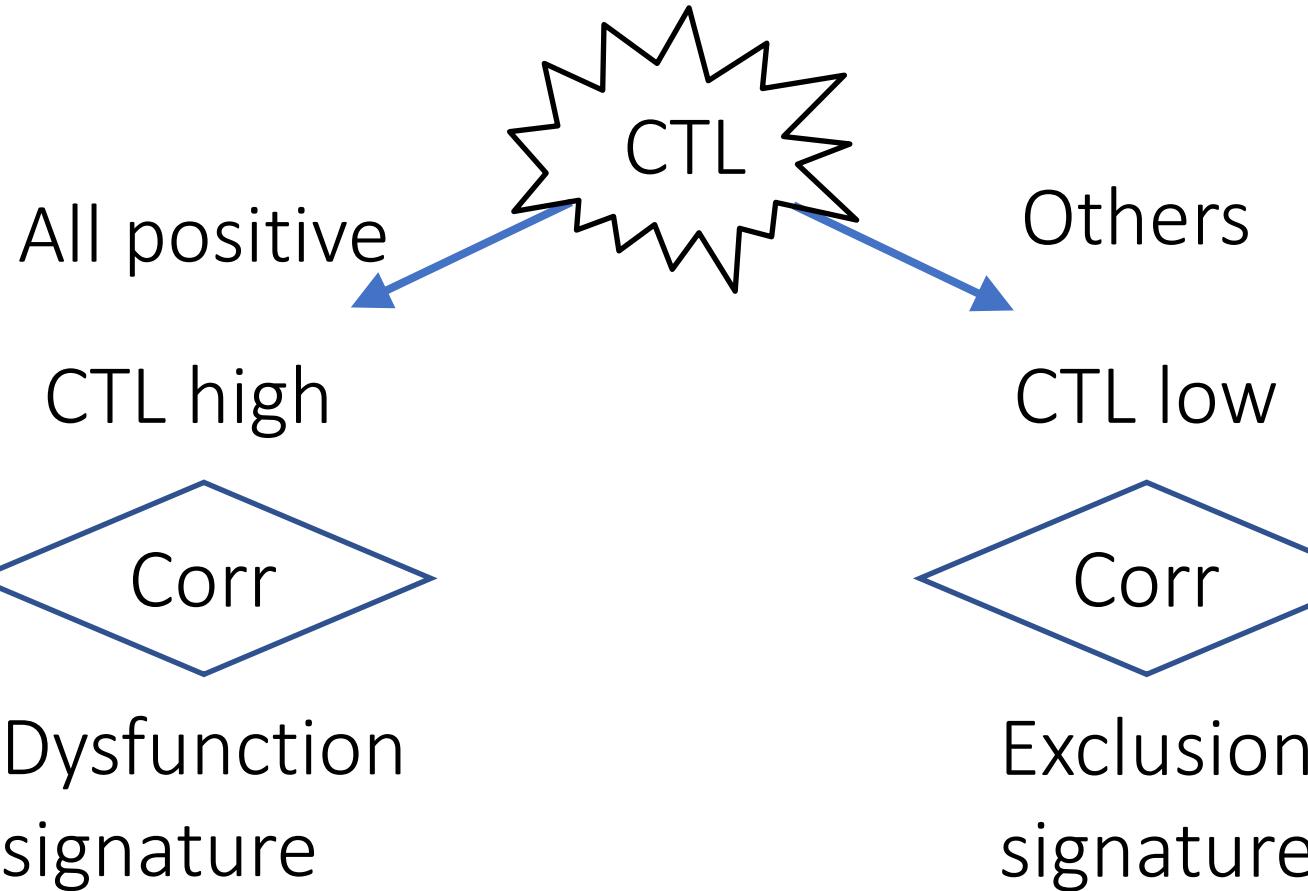
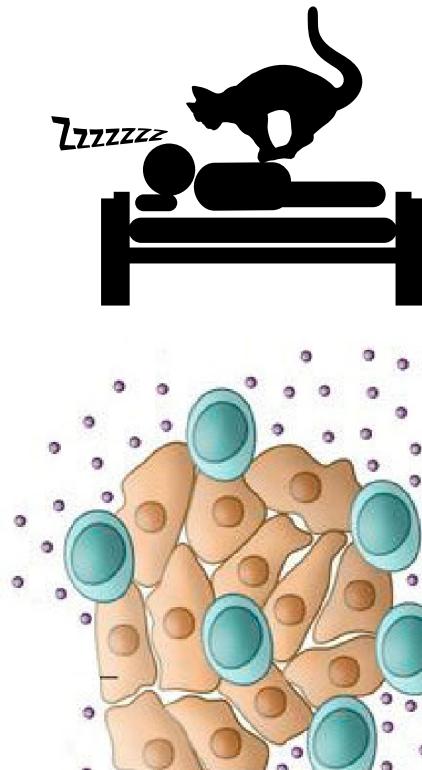
(Gajewski, Schreiber, Fu et al., 2013)

# TIDE: Tumor Immune Dysfunction and Exclusion



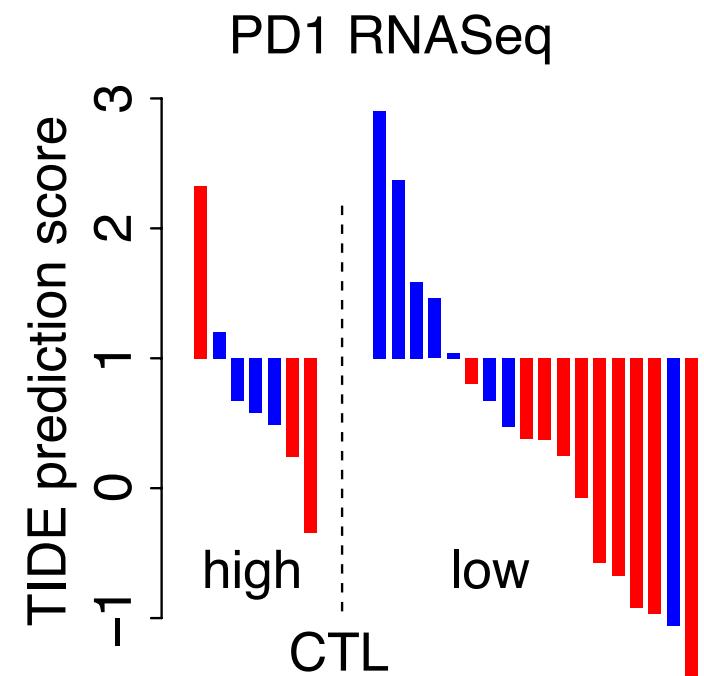
# Prediction with a Two-Part Procedure

*CD8A, CD8B, GZMA, GZMB, PRF1*

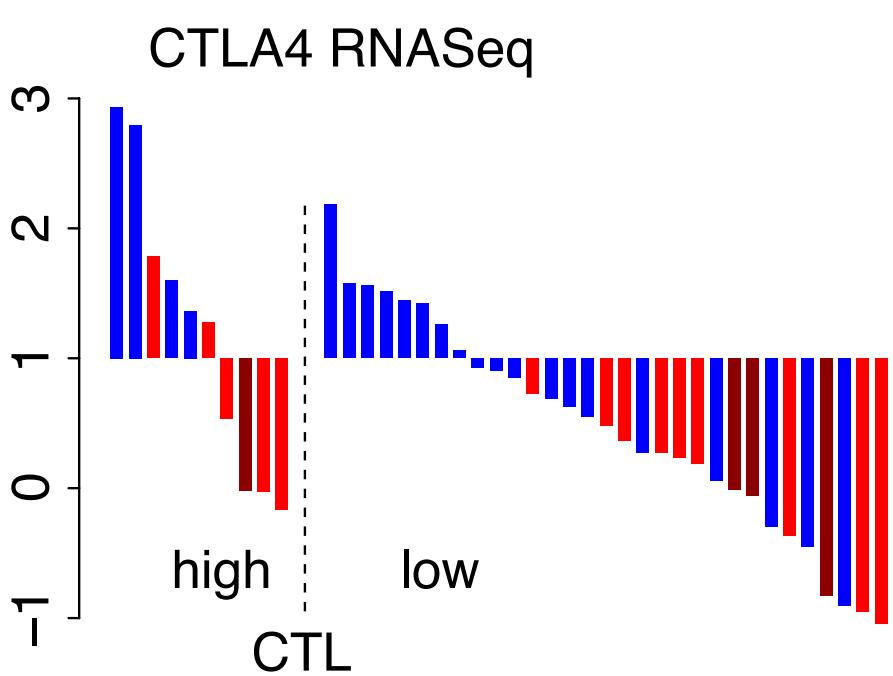


# TIDE Scores of Pre-Treatment Tumors

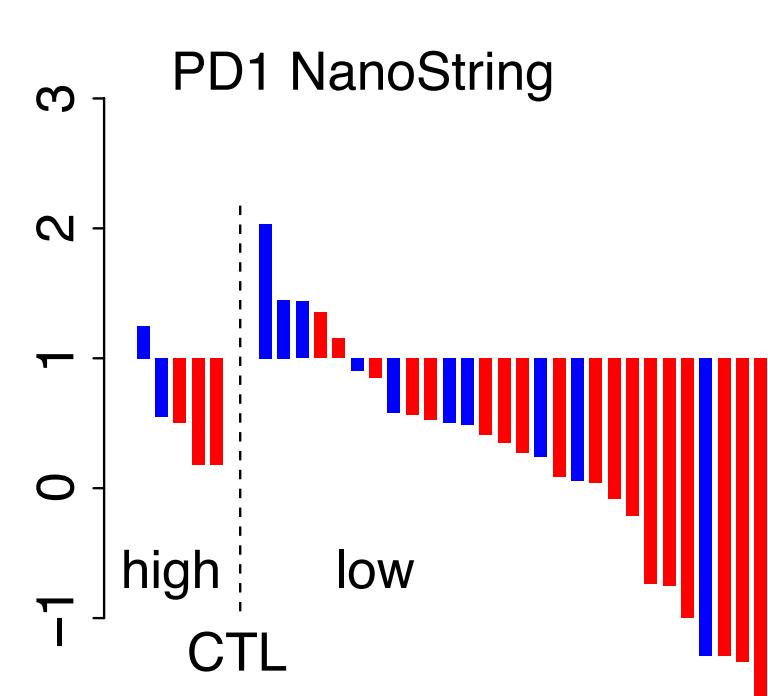
Hugo et al., 2016 n = 25



VanAllen et al., 2015 n = 42

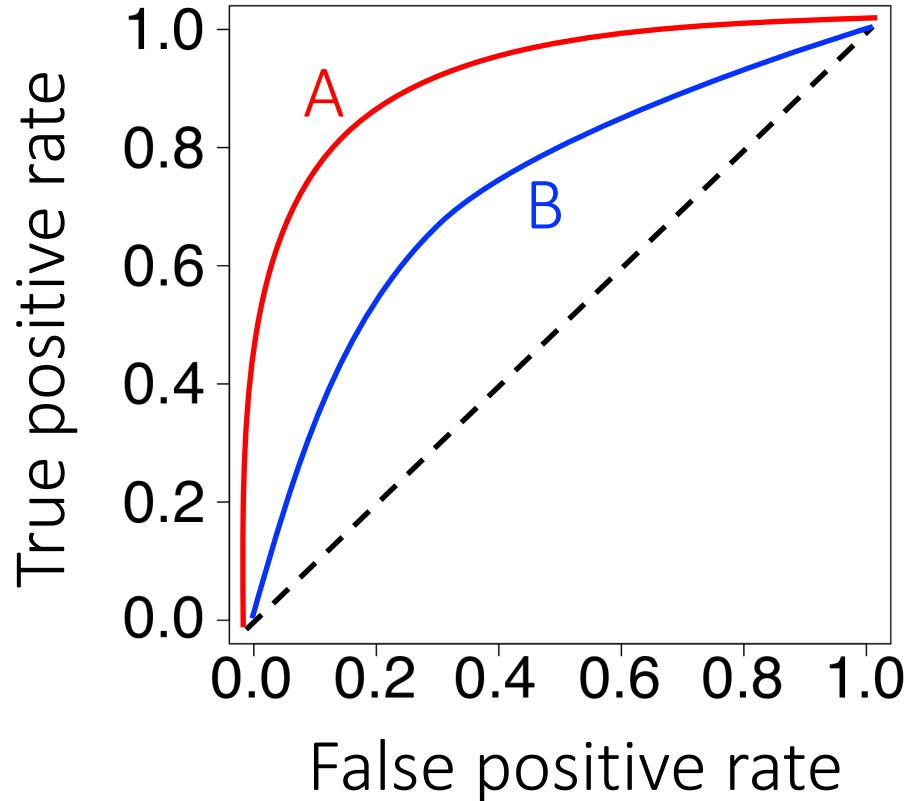


Prat et al., 2017 n = 33

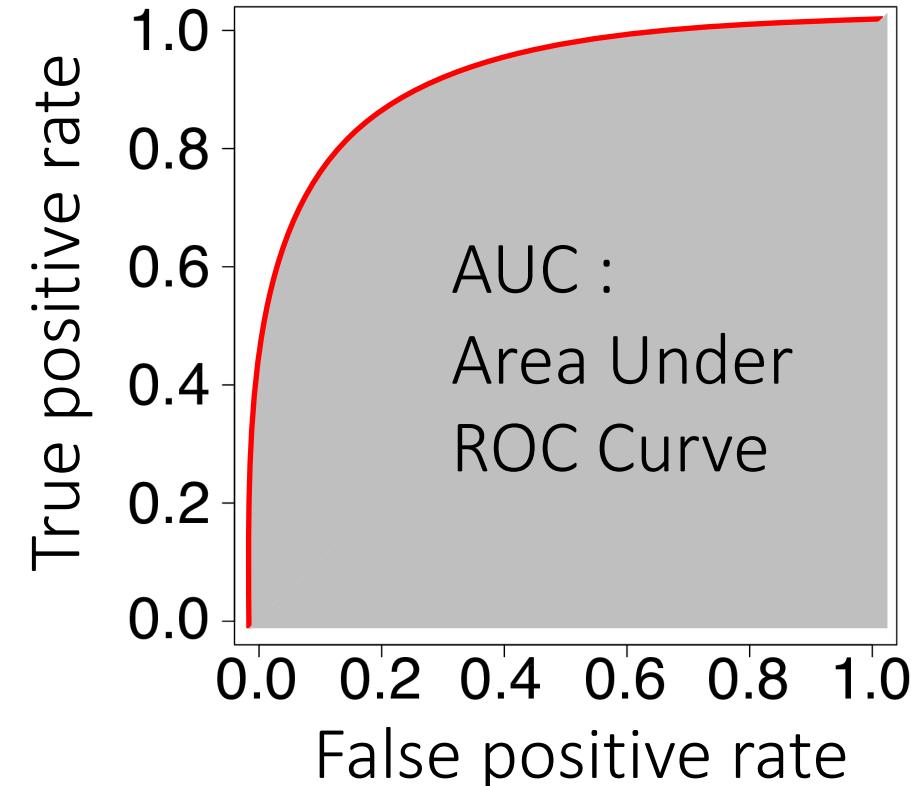


■ Responder      ■ Non-responder  
■ Long-survival

# Receiver Operating Characteristic (ROC) Curve

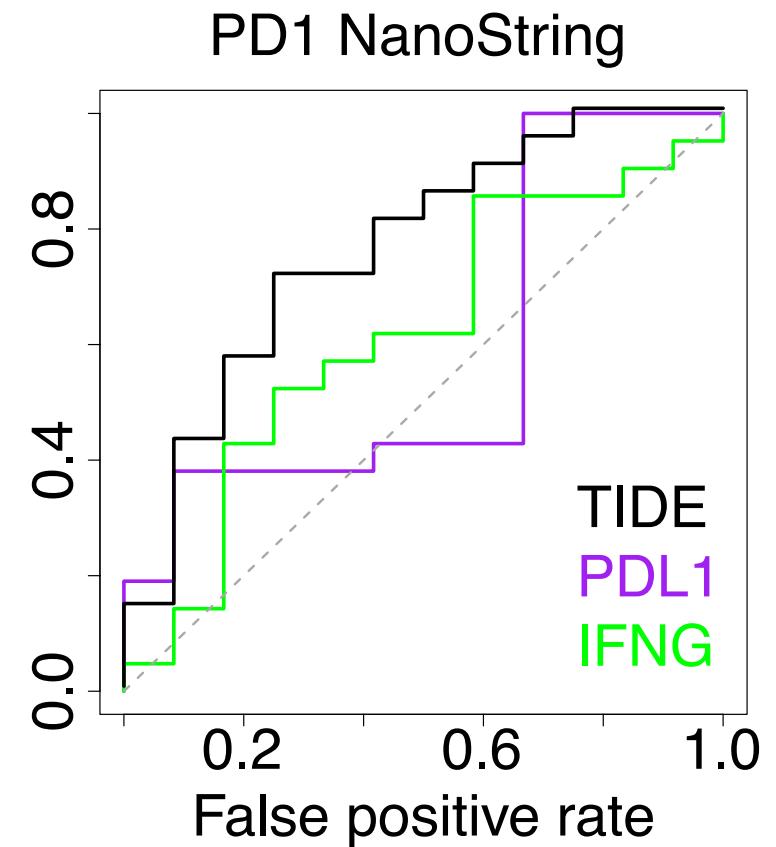
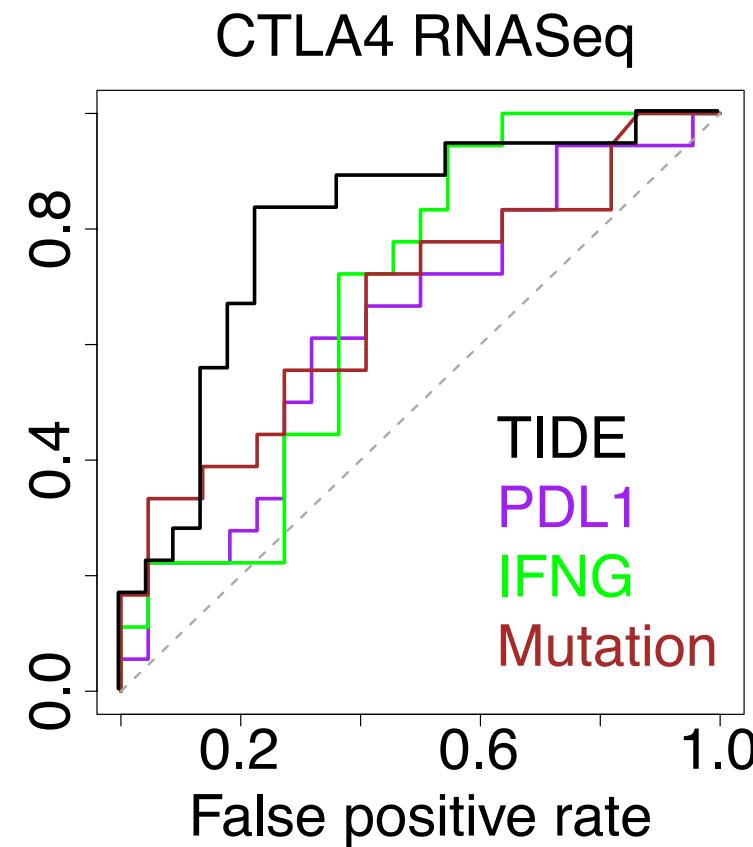
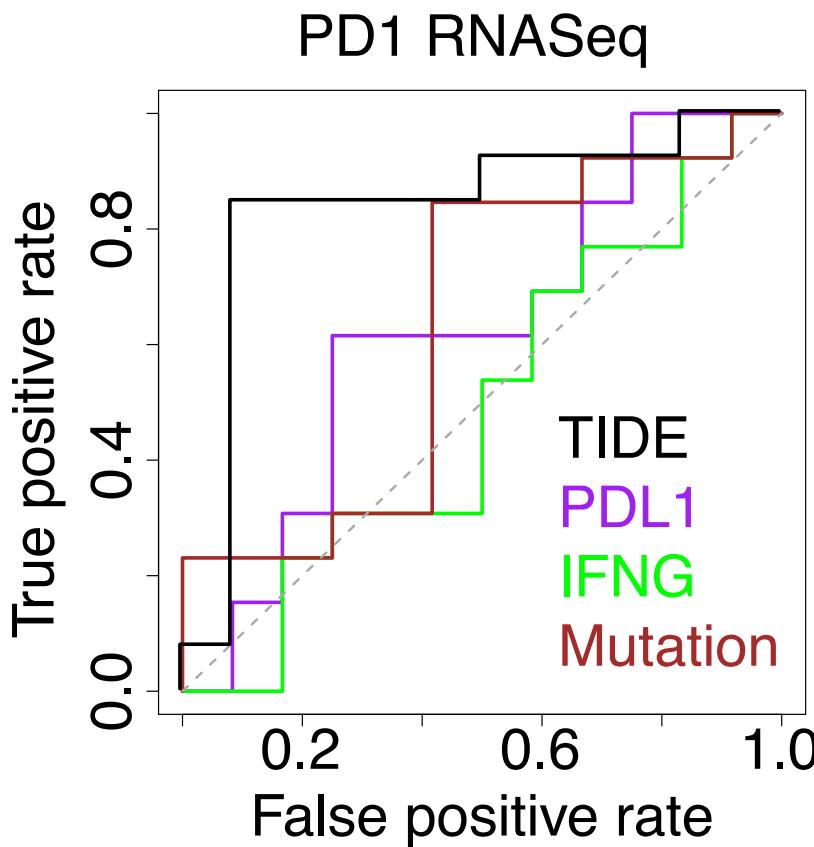


Biomarker A is better than Biomarker B

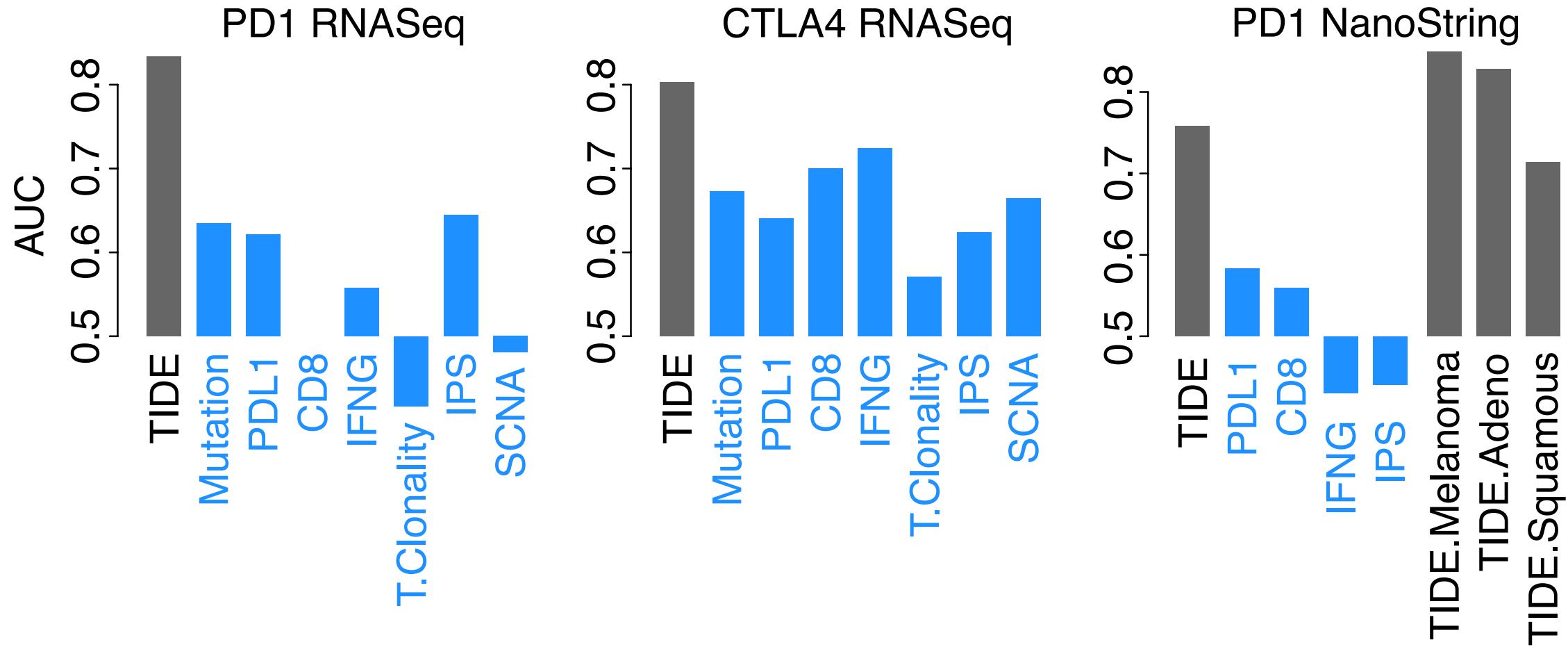


From 0 to 1 with random performance as 0.5

# TIDE outperforms other biomarkers

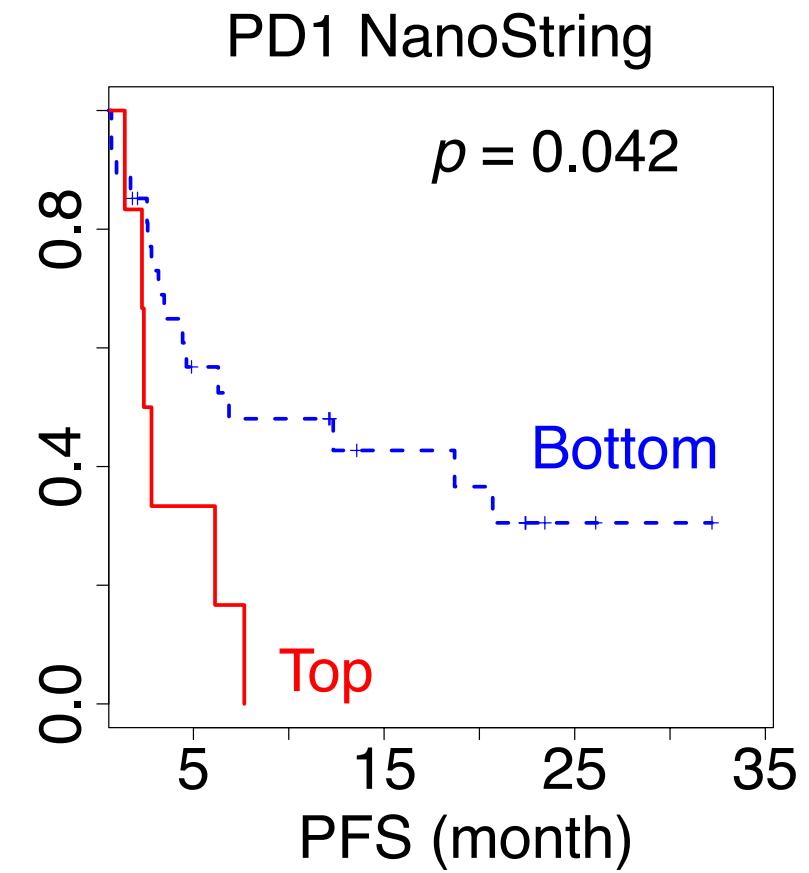
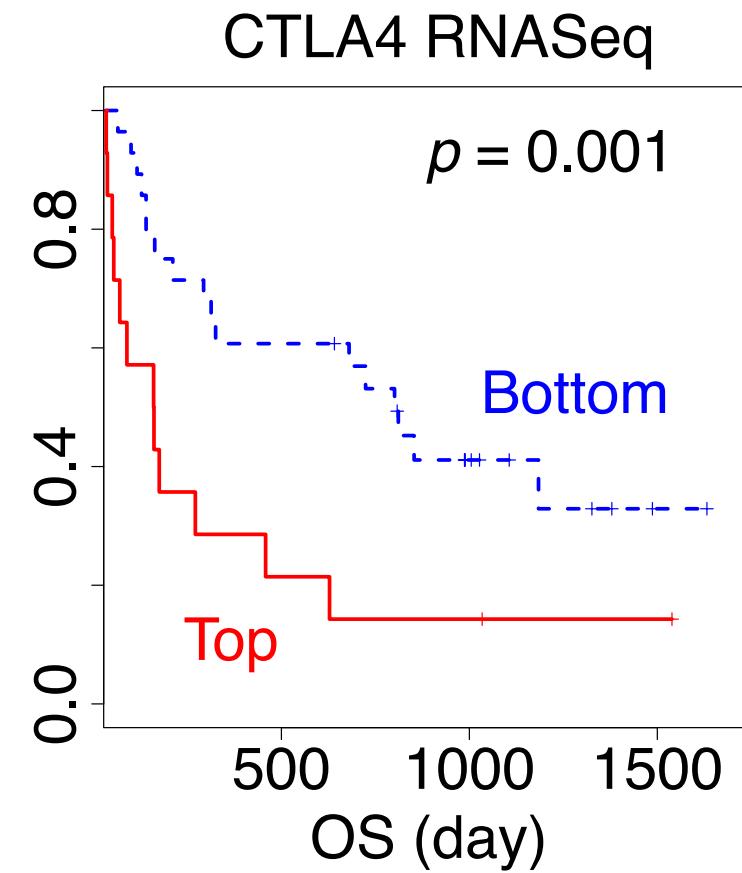
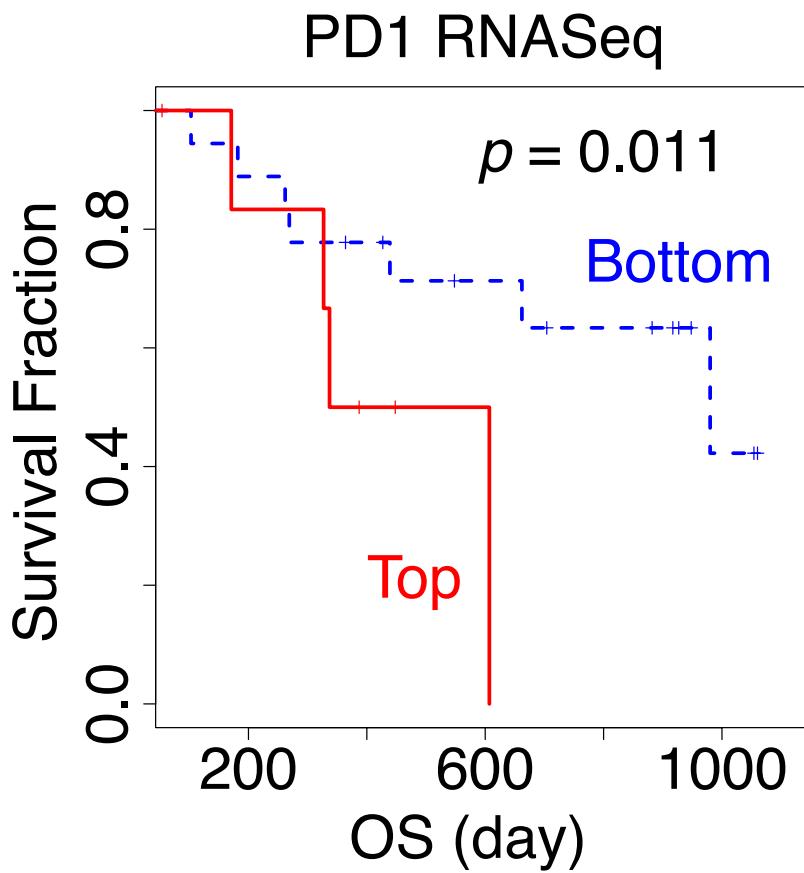


# TIDE outperforms other biomarkers

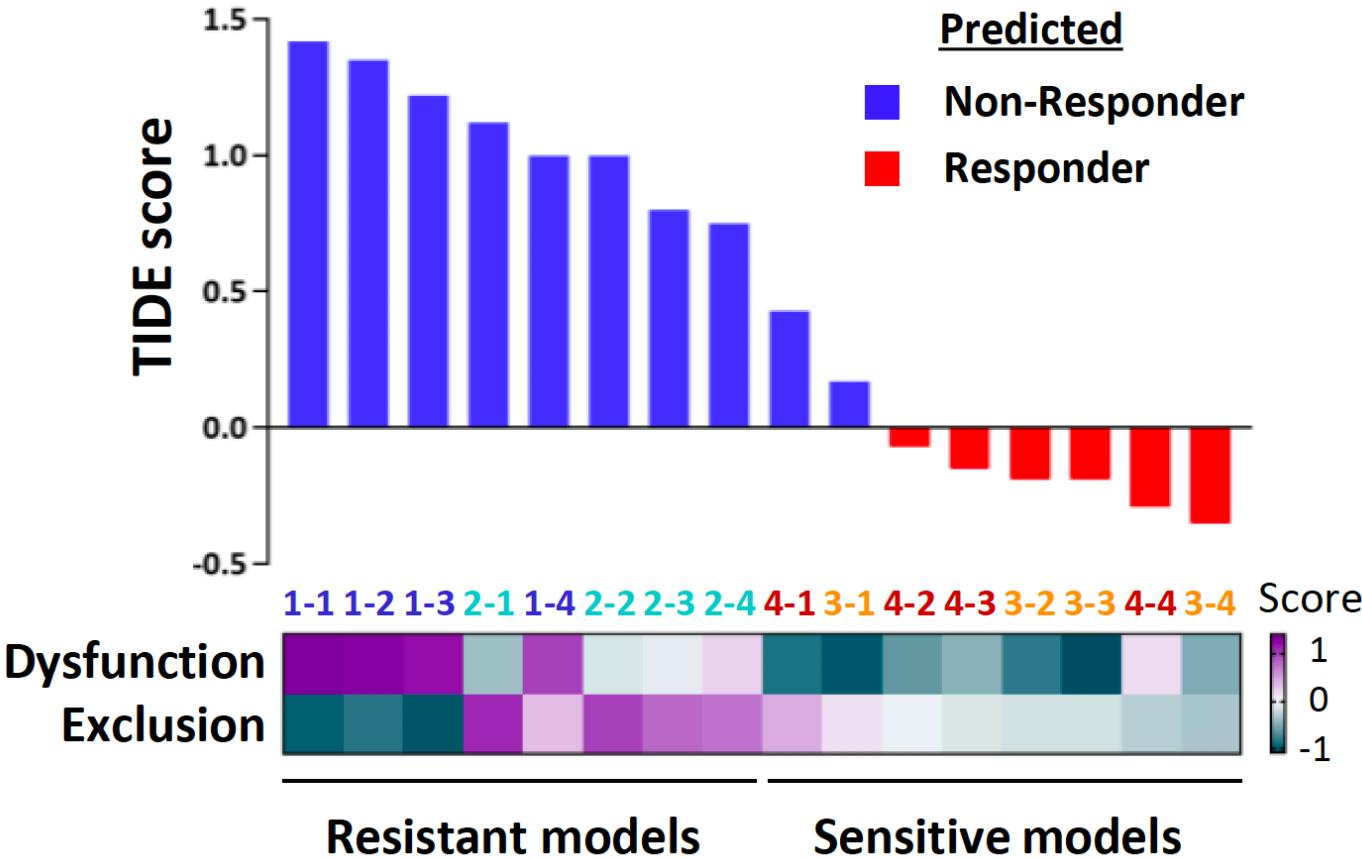


**Mutation:** nonsynonymous mutation load; **PDL1:** PD-L1 expression; **CD8:** CD8A + CD8B expression;  
**IFNG:** interferon gamma response expression signature (Ayers et al. 2017); **T.Clonality:** Clonality of T cell receptor;  
**IPS:** ImmunePhenoScore (Charoentong et al. 2017); **SCNA:** variation of copy number alterations (Davoli et al. 2017).

# TIDE can predict patient overall survival

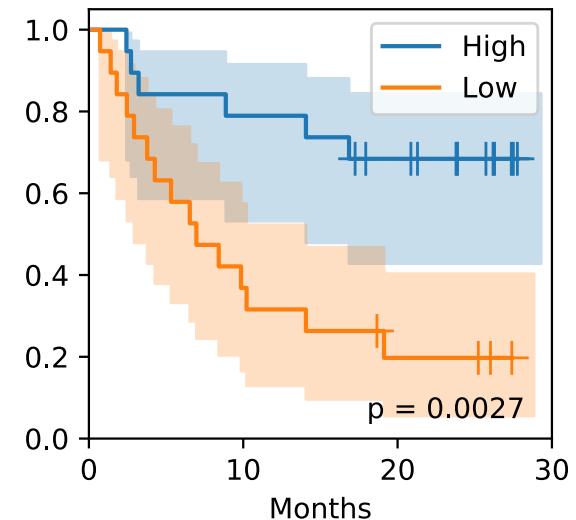


# Independent validation of TIDE

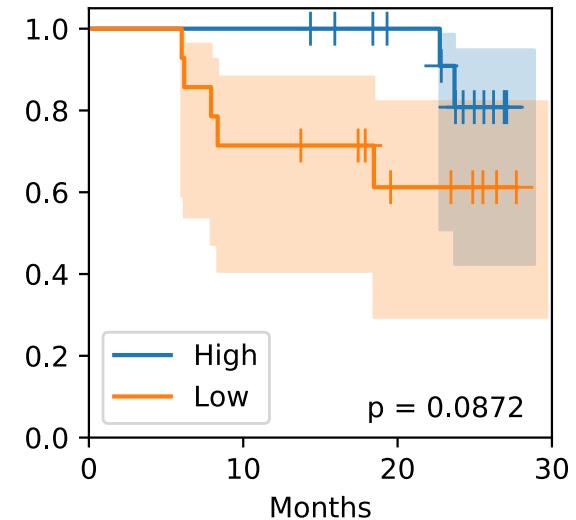


Eva Pérez-Guijarro et al., Nature Medicine 2020 @ Glenn Merlino Lab

IPILOMUMAB-NIVOLUMAB  
Geneset



NIVOLUMAB-IPILOMUMAB  
Geneset

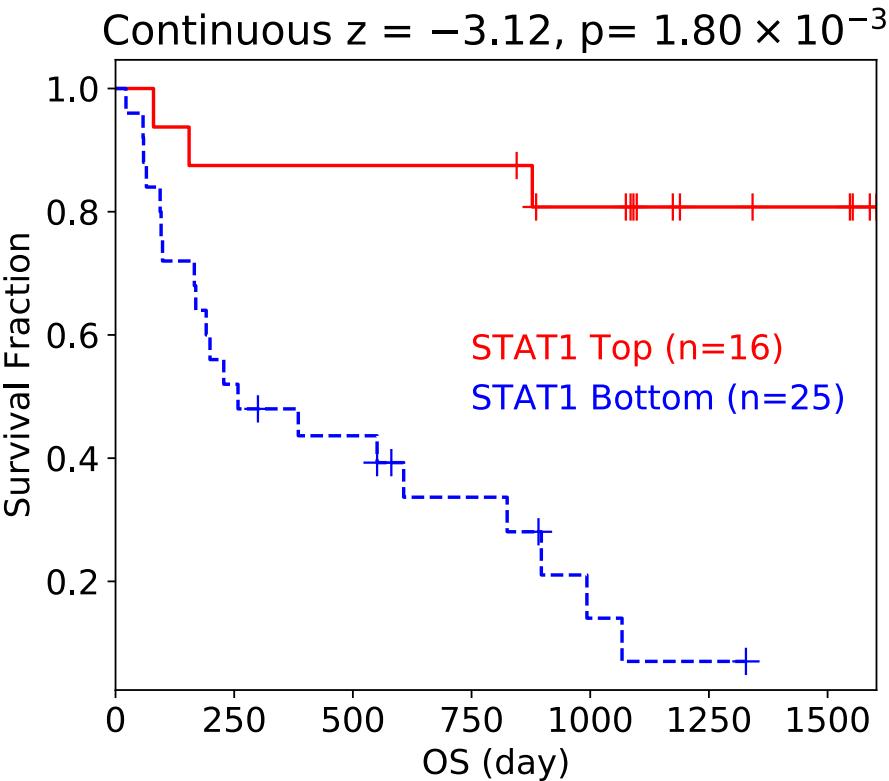


# Immunotherapy Clinical Cohorts Example : STAT1

## Result for query: STAT1 (6772)

We listed the high confidence scores in immunotherapy.

Core	Expression
Association between gene expression and survival	
Click table header to sort	
◆ Cohort	
Gide2019_PD1+CTLA4	
Gide2019_PD1+CTLA4	
Mariathasan2019	
Liu2019	
Nathanson2017	
Gide2019_PD1+CTLA4	
Lauss2017	
Lauss2017	
Riaz2017_PD1	
VanAllen2015_CTL4	
VanAllen2015_CTL4	
Liu2019_PD1	
Gide2019_PD1+CTLA4	
Nathanson2017_CTL4	
Riaz2017_PD1	



Also included several reference results, including Reaction.

Gene	Reaction	Risk	Risk.adj	Count
STAT1	PD1	-0.851	41	
STAT1	CTLA4	-2.084	41	
STAT1	PD1+CTLA4	-2.474	-1.268	348
STAT1	Anti-PD1	-1.909	-0.247	47
STAT1	Anti-CTLA4	-1.678	0.657	15
STAT1	Anti-PD1+CTLA4	-1.673	-0.887	32
STAT1	Anti-PD1	-1.608	-2.219	25
STAT1	Anti-CTLA4	-1.543	-1.634	25
STAT1	Anti-PD1+CTLA4	-1.377	-0.367	26
STAT1	Anti-PD1	-1.371	0.391	42
STAT1	Anti-CTLA4	-1.313	-0.124	42
STAT1	Anti-PD1+CTLA4	-1.089	0.062	47
STAT1	Anti-PD1	-0.956	-0.237	32
STAT1	Anti-CTLA4	-0.803	-1.576	9
STAT1	Anti-PD1+CTLA4	-0.752	-0.753	25

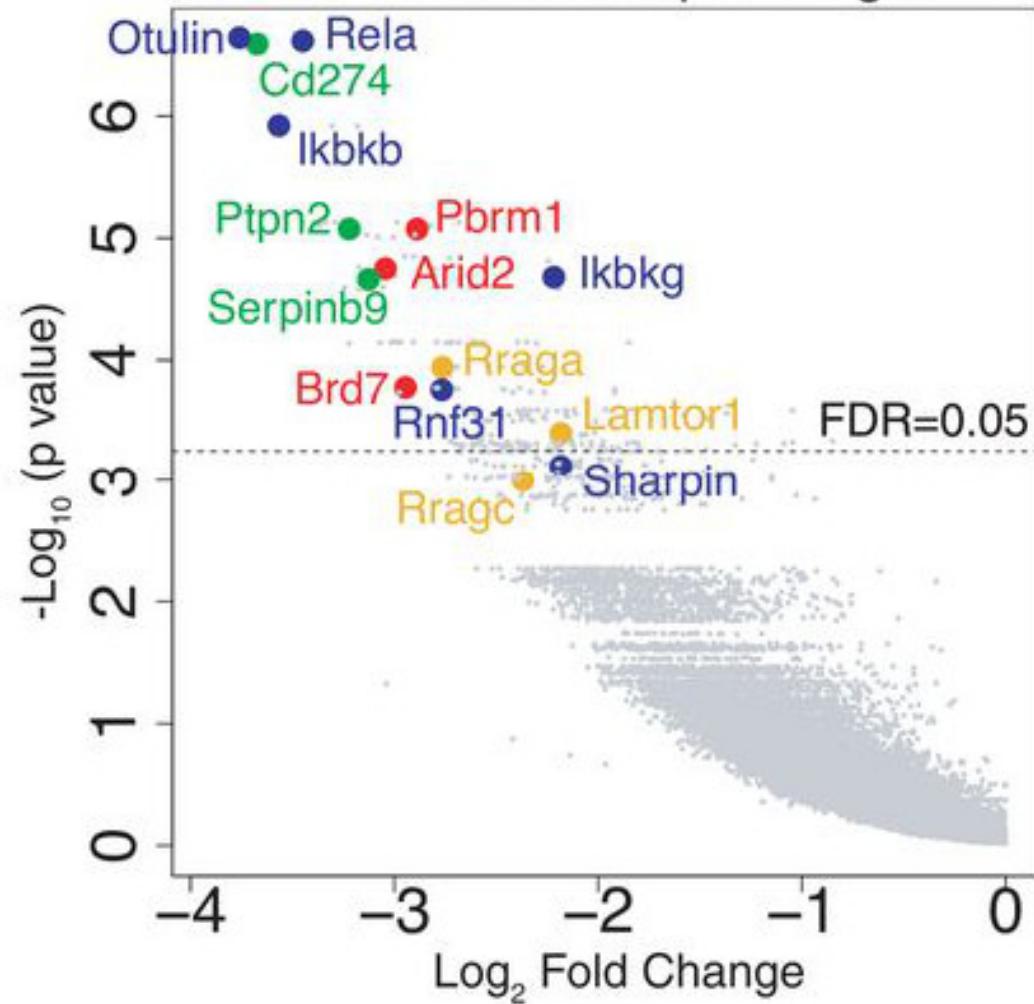
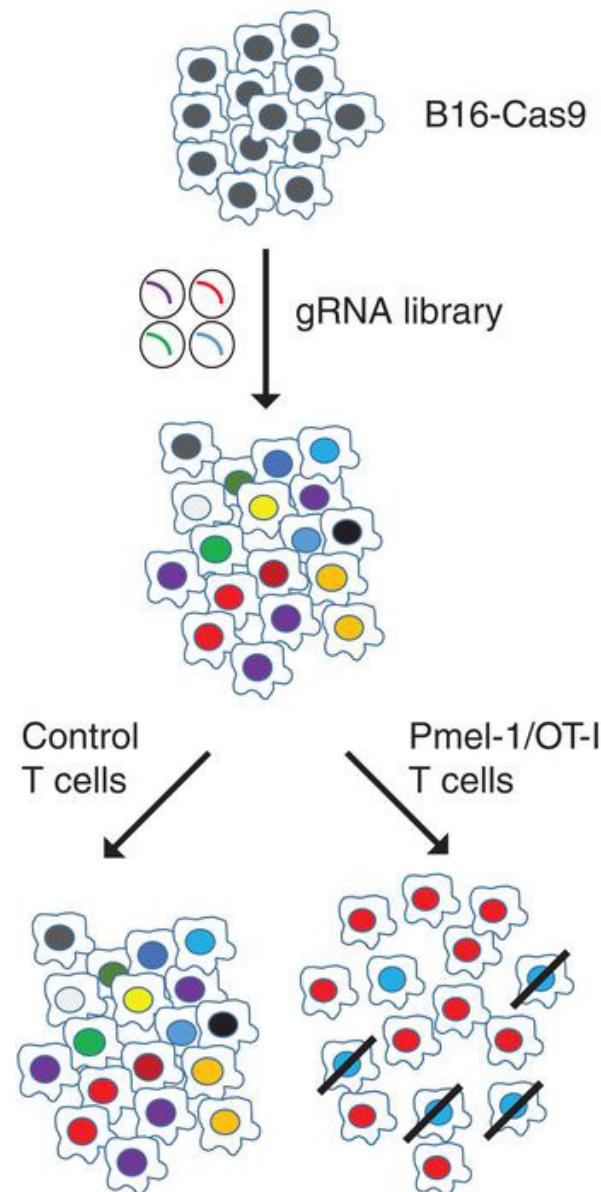
# CRISPR Screens

## Example: STAT1

Core	Expression	Copy_Number	Methylation	Exclusion	Ref_Therapy	Ref_Screen
Gene knockout phenotype from genetic screens profiling regulators of T-cell mediated tumor killing						
Click table header for sorting. Hover your mouse on a cell for description or full name of abbreviation.						
♦ Cohort	♦ Cancer	♦ Model	♦ Condition	♦ logFC	♦ Z-score	
Pan 2018	Melanoma	B16	Pmel1	8.801	13.217	
Freeman 2019	Melanoma	B16	OT1	12.215	8.91	
Manguso 2017	Melanoma	B16	GVAX+PD1	2.393	5.924	
Pech 2019	Leukemia	K562	NK_E:T=2.5	1.521	5.782	
Pan 2018	Melanoma	B16	OT1	2.616	5.046	
Pech 2019	Leukemia	K562	NK_E:T=1	0.987	4.122	
Manguso 2017	Melanoma	B16	GVAX	1.199	3.615	
Patel 2017	Melanoma	Mel624	1	0.513	3.492	
Kearney 2018	Colon	MC38	T_IgG	4.193	2.903	
Kearney 2018	Colon	MC38	T_PD1	4.329	2.795	
Patel 2017	Melanoma	Mel624	2	0.255	1.462	
Shifrut 2018	Donor	T cell	Average	0.214	1.346	
Vredevoogd 2019	Melanoma	D10 IFNGR1-	MART1	0.231	1.344	
Meyers 2017	Mix	Cell panel	Essentiality	0.126	0.459	
Kearney 2018	Colon	MC38	NK_20	0.963	0.376	
Kearney 2018	Colon	MC38	NK_10	0.322	0.238	
Freeman 2019	Melanoma	B16	NK	-1.425	-1.055	

Export to CSV

# CRISPR screen for T-cell mediated tumor killing



Pan\*, Kobayashi\*, Jiang\* et al., *Science*, 2018

# Gene Prioritization

Putting everything together

[Response Prediction](#)[Query Gene](#)[Regulator Prioritization](#)[Biomarker Evaluation](#)[Download](#)[FAQ](#)[Contact](#)[News](#)[Peng J](#)

## README

### Input

- Input a gene set with whole Entrez ID or whole official gene symbol. (**separated by ","**)
- Example:
- Manually Input:

```
PTPN2, AXL, EPHA3, CACNA1G, DNMT3A, EPHA2, PDE1B, ROR2, HTRA1, GZMM, KCNK2, KCNF1, SV2A, CLCNKB, SCN9A, SCN2A, HDAC3, PADI4, GRM1, HRH1
```

- Gene set file:

[Download](#)

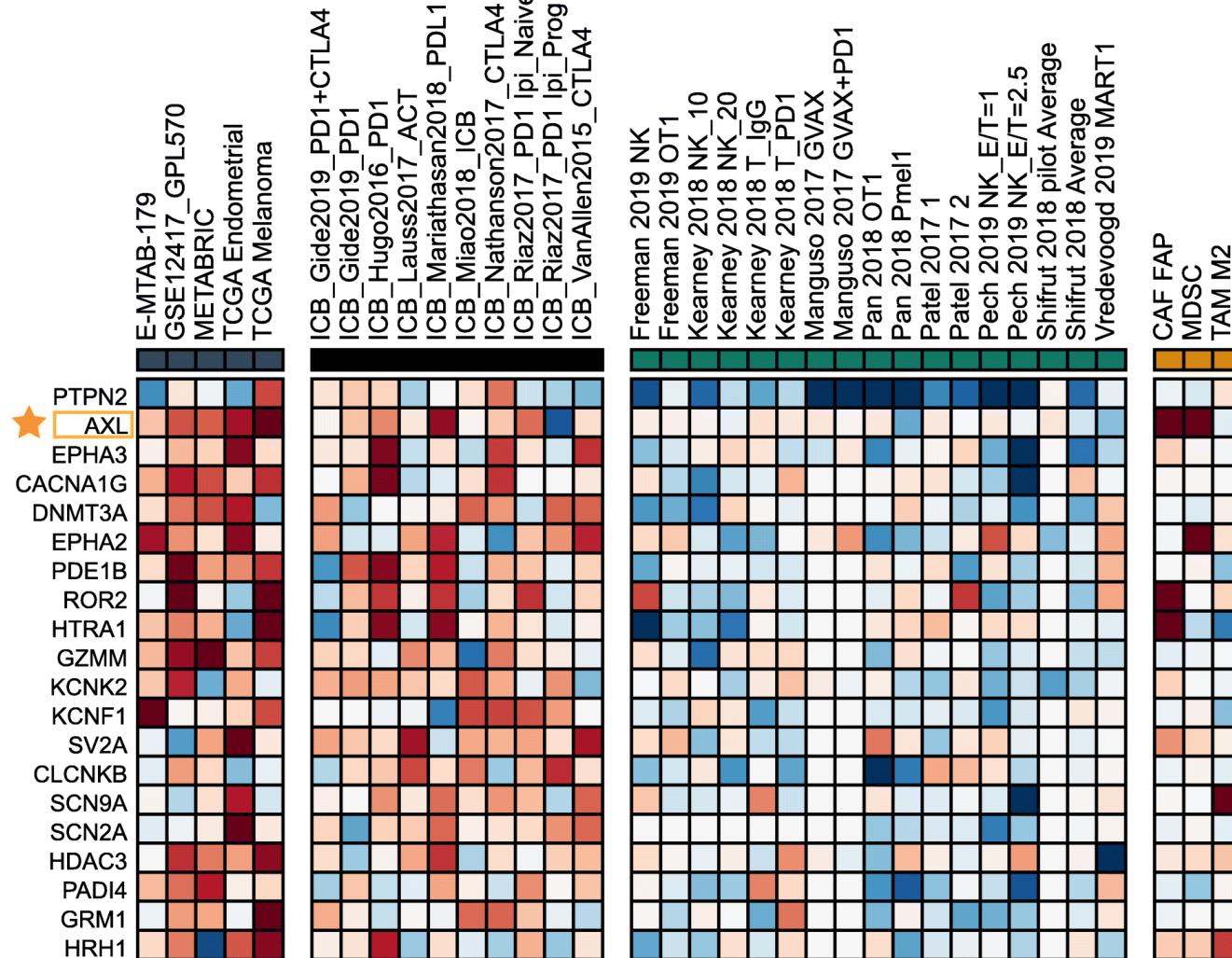
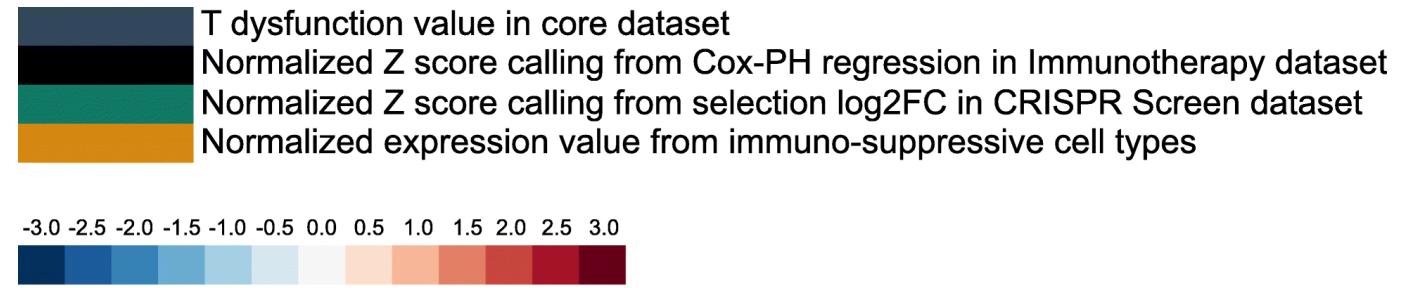
## RUN

### Manually input Genes

OR

[Upload Geneset File](#)[Submit](#)

# Gene Prioritization



# Biomarker Evaluation



## Function on TIDE



Karen Li  
Shirley Liu Lab

[Download the video](#)

TGFB1,-1

PDL1,1

FAP,-1

VEGFA,-1

IFNG,1

ANGPT2,-1

[Download](#)

## README

- 1 Input genes that you are interested.(Using comma to separate genes. eg. PD1, CTLA4) or upload a gene file.
- 2 This function will use the average/weighted(if a gene file was uploaded ) expression of the custom geneset as a new biomarker.
- 3 Comparing the new biomarker with existed biomarkers, showing bar plots.
- 4 You can download interested plots by clicking the  button.
- 5 By clicking each point in the survival plot, you can view the corresponding Kaplan Meier plot on the top.

Manually input Genes

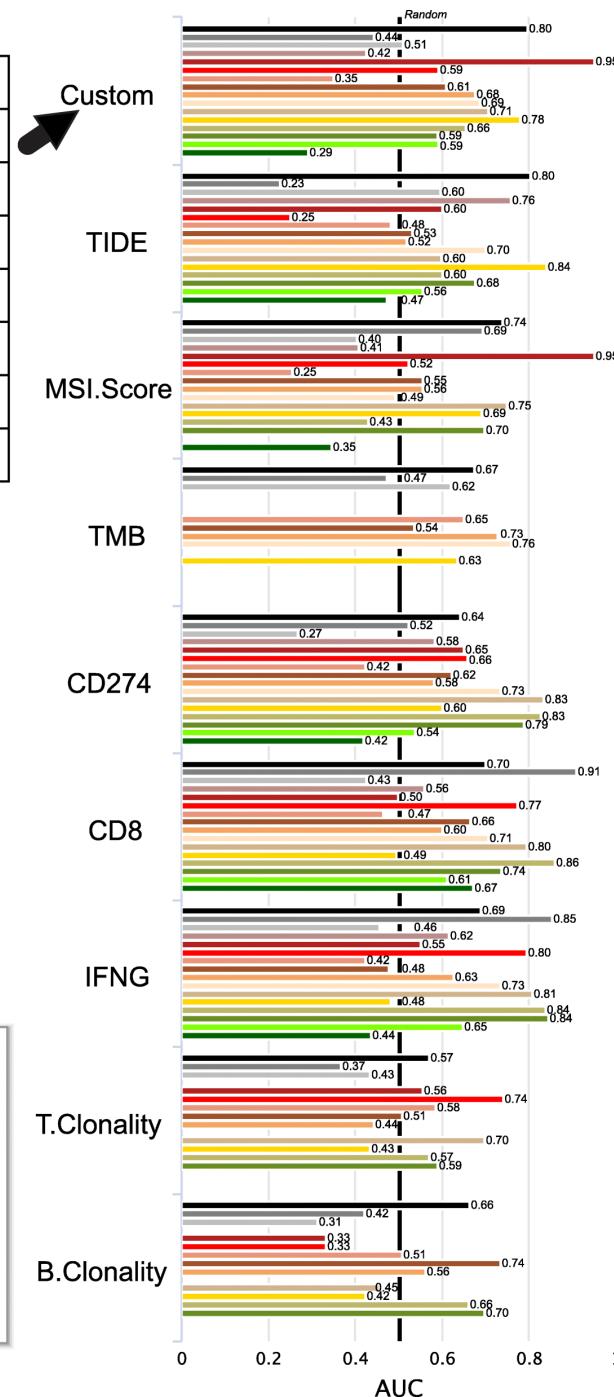
OR

 [Submit](#)

# Biomarker Comparison

Gene	Weight
SERPINB9	-1.0
TGFB1	-1.0
PDL1	1.0
FAP	-1.0
VEGFA	-1.0
IFNG	1.0
ANGPT2	-1.0

- VanAllen2015\_CTL4\_Melanoma
- Riaz2017\_PD1\_Melanoma\_Ipi.Prog
- Riaz2017\_PD1\_Melanoma\_Ipi.Naive
- Prat2017\_PD1\_NSCLC-HNSC-Melanoma\_Nanostring
- Nathanson2017\_CTL4\_Melanoma\_Pre
- Nathanson2017\_CTL4\_Melanoma\_Post
- Miao2018\_ICB\_Kidney\_Clear
- McDermott2018\_PDL1\_Kidney\_Clear
- Mariathasan2018\_PDL1\_Bladder\_mUC
- Lauss2017\_ACT\_Melanoma
- Kim2018\_PD1\_Gastric
- Hugo2016\_PD1\_Melanoma
- Gide2019\_PD1\_Melanoma
- Gide2019\_PD1+CTL4\_Melanoma
- Chen2016\_PD1\_Melanoma\_Nanostring\_Ipi.Prog
- Chen2016\_CTL4\_Melanoma\_Nanostring



# Biomarker Comparison : Survival Plot

Running successfully:

- Input: gene\_weight.txt

Warning

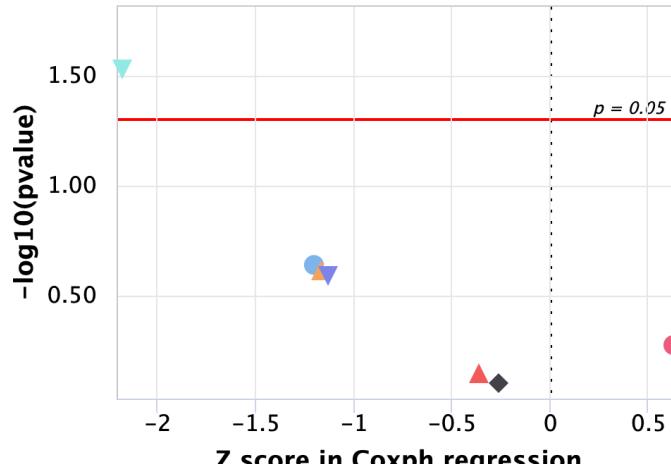
- 85.7% genes were mapped in Chen2016\_PD1\_Melanoma\_Nanostring\_lpi.Prog<br>Pos=6,Neg=9
- 85.7% genes were mapped in Chen2016\_CTL4\_Melanoma\_Nanostring<br>Pos=5,Neg=11
- 57.1% genes were mapped in Prat2017\_PD1\_NSCLC-HNSC-Melanoma\_Nanostring<br>Pos=21,Neg=12

- Click to start new running.

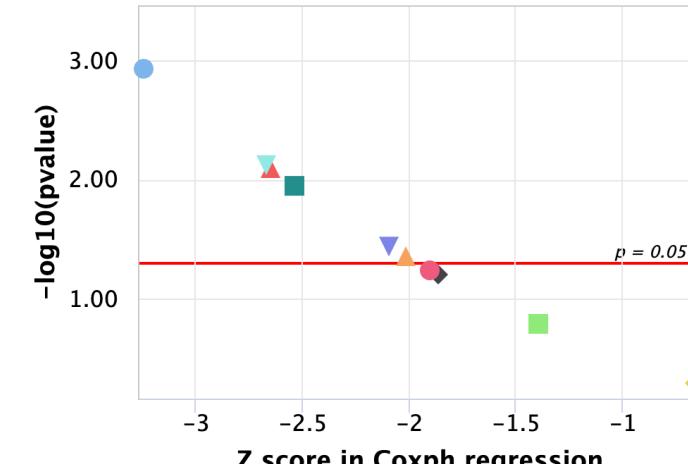
Response

Overall Survival (OS)

Zhao2019\_PD1\_Glioblastoma  
Pos=10,Neg=7  
(OS)



VanAllen2015\_CTL4\_Melanoma  
Pos=19,Neg=23  
(OS)



TIDE    MSI.Score    Mutation    CD274  
CD8    IFNG    T.Clonality    B.Clonality  
Merck18    Custom

TIDE    MSI.Score    Mutation    CD274  
CD8    IFNG    T.Clonality    B.Clonality  
Merck18    Custom

Some online demo

# 2: Cell Signaling Research Platform

<https://cellsig-dev.ccr.cancer.gov> (temporary domain, only within NIH firewall)

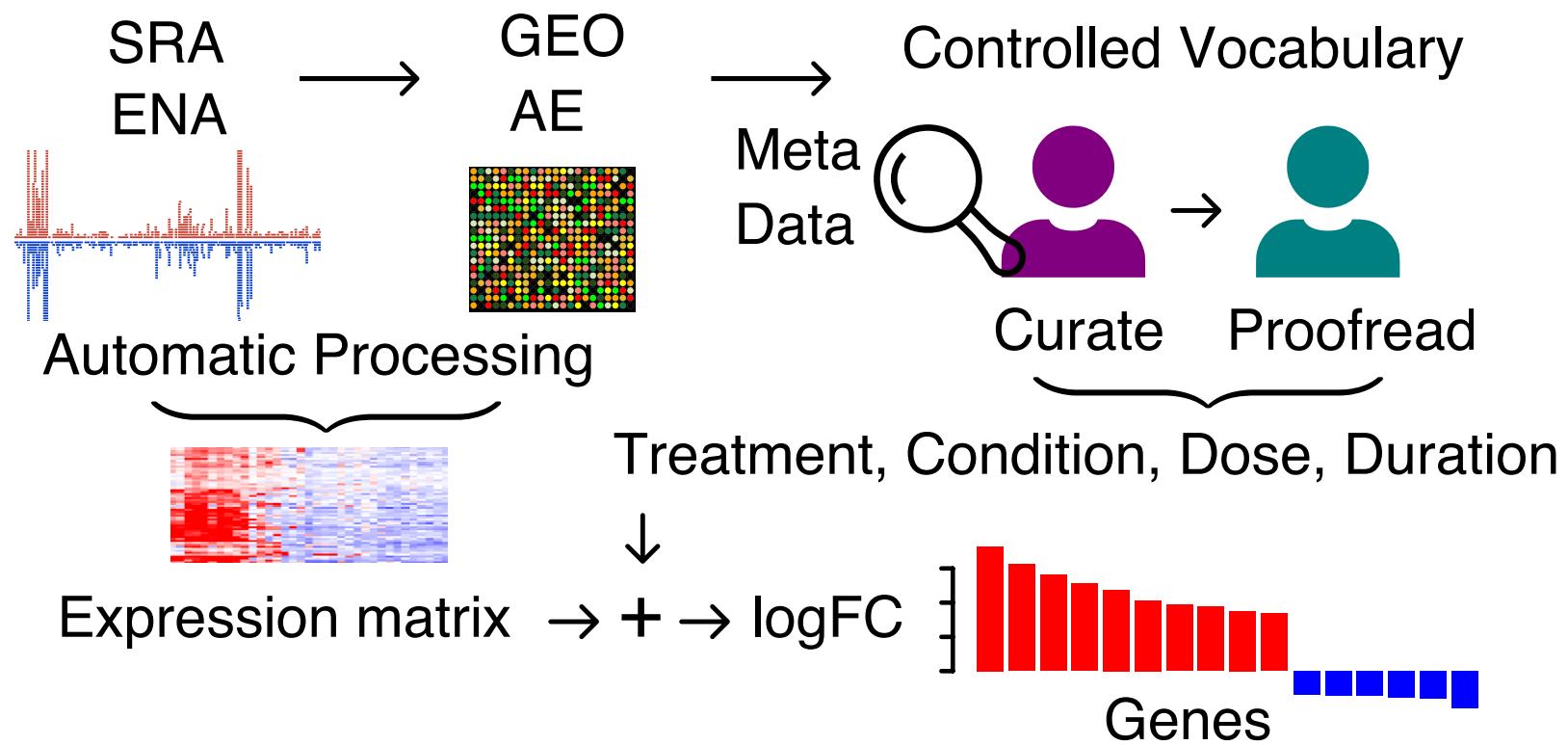
NIH > NATIONAL CANCER INSTITUTE  Cell Signaling Database

OVERVIEW SEARCH RUN DOWNLOAD CONTACT  PENG\_JIANG LOGOUT

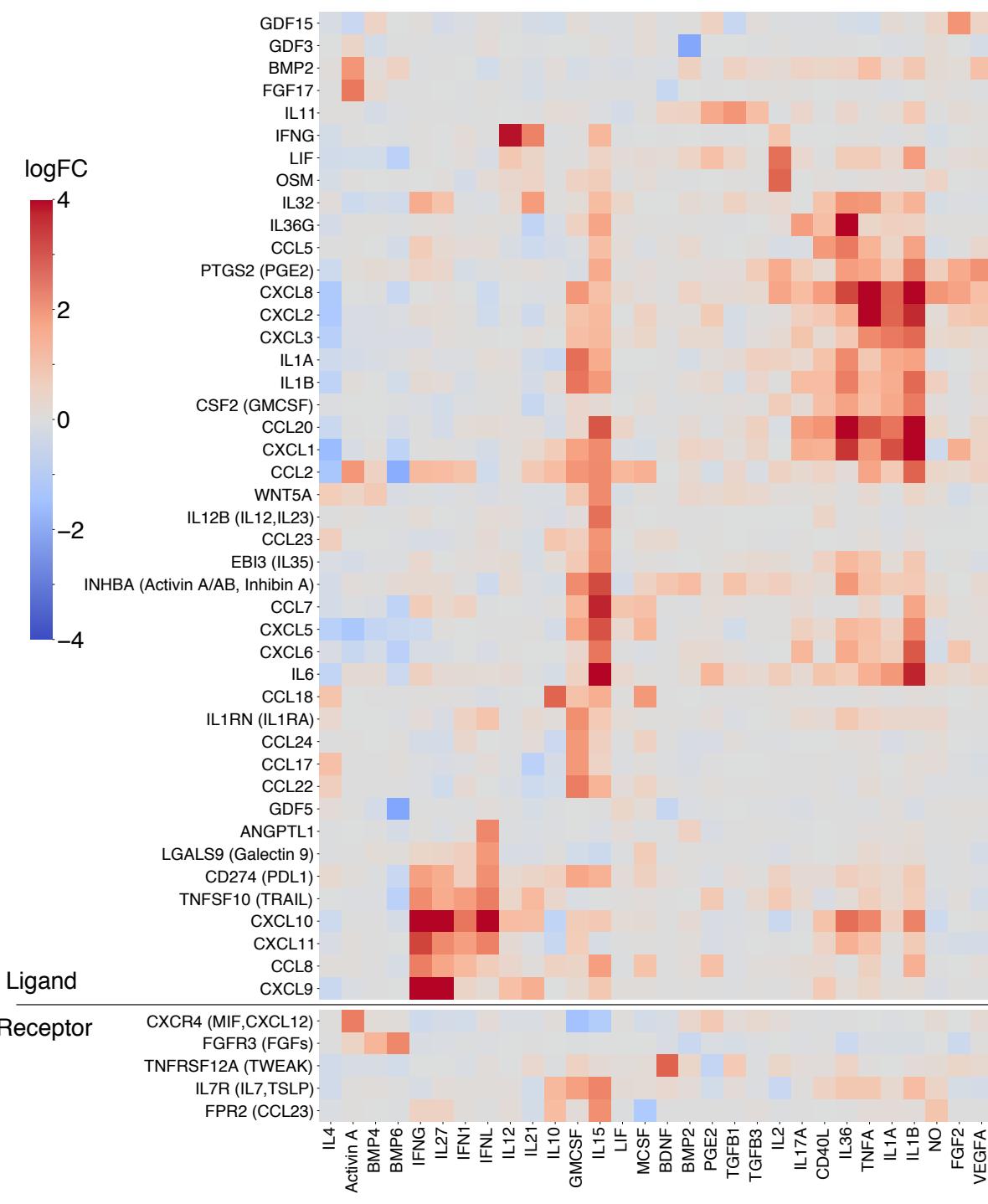
The CellSig (**Cell Signaling**) platform aims to help biologists to study the cellular response to signaling molecules (e.g., cytokines, chemokines, and growth factors), leveraging the public expression data from treatment experiments deposited in the NCBI GEO and ArrayExpress databases. You can query cell signals and analyze genes induced or repressed ([SEARCH module](#)). You can also input a gene expression profile, and analyze the enriched signals, leveraging the treatment response profiles collected ([RUN module](#)).

U.S. Department of Health and Human Services | National Institutes of Health | National Cancer Institute | USA.gov

# Data Collection



# Response within signaling molecules



# Gene Query

 **NATIONAL CANCER INSTITUTE**  **Cell Signaling Database**

OVERVIEW    SEARCH    RUN    DOWNLOAD    CONTACT     PENG\_JIANG    LOGOUT

In the search module, you can query either a cell **signal molecule** (e.g., *TGFB*) or a **target gene** (e.g., *SOX4*). With a cell signal molecule as the input, the platform will report the log2 fold change (logFC) of target genes upon treatments from that signal in all collected studies. Please use the auto-complete function in the input box for available signal names. With a target gene as the input, the platform will report the logFC upon the treatment of all cell signals.

*something like TGFB or SOX4*

**Search**

# Signal Prediction



*Cell* Signaling Database

OVERVIEW

SEARCH

RUN

DOWNLOAD

CONTACT



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LOGOUT

Please upload a matrix file with columns as samples and rows as genes. The value separator should be the tab, and the gene names should follow the standard gene symbols. The platform accepts Gzip files as input. Please see a [sample file here](#). The file size should be smaller than 10MB, and the number of samples should be less than 20. If you need to analyze more samples or complicated functions (e.g., background correction), please [download](#) our software and run locally.

Note: We recommend input differential profiles between the two conditions. If your data is from a collection of samples without pairs, please mean-centralize the value of each gene across all samples or apply background correction available in the download version (Refer to the help document for details).

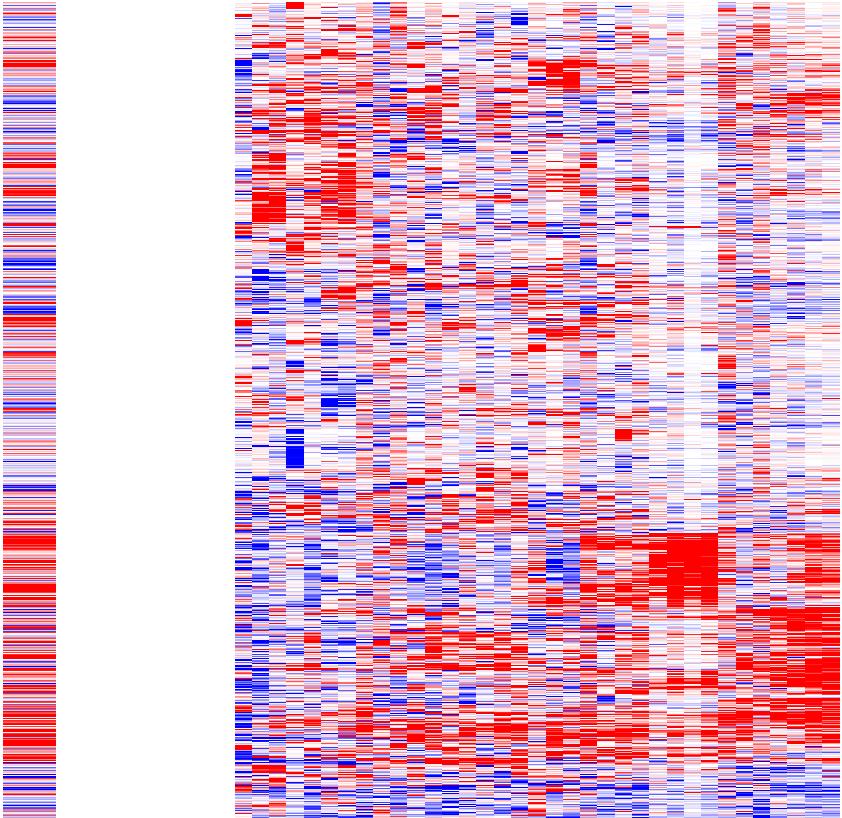
Task\_file:

Choose File No file chosen

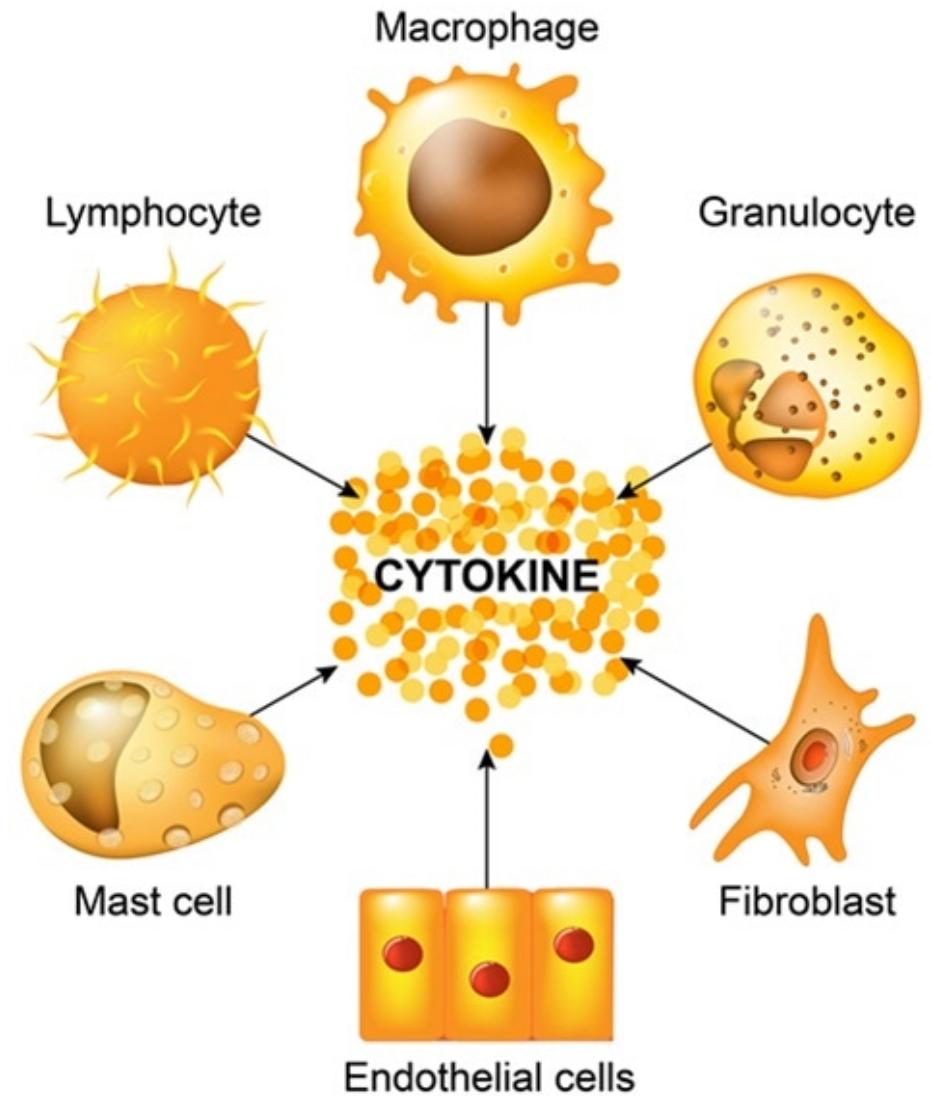
**Submit**

# Signal Prediction

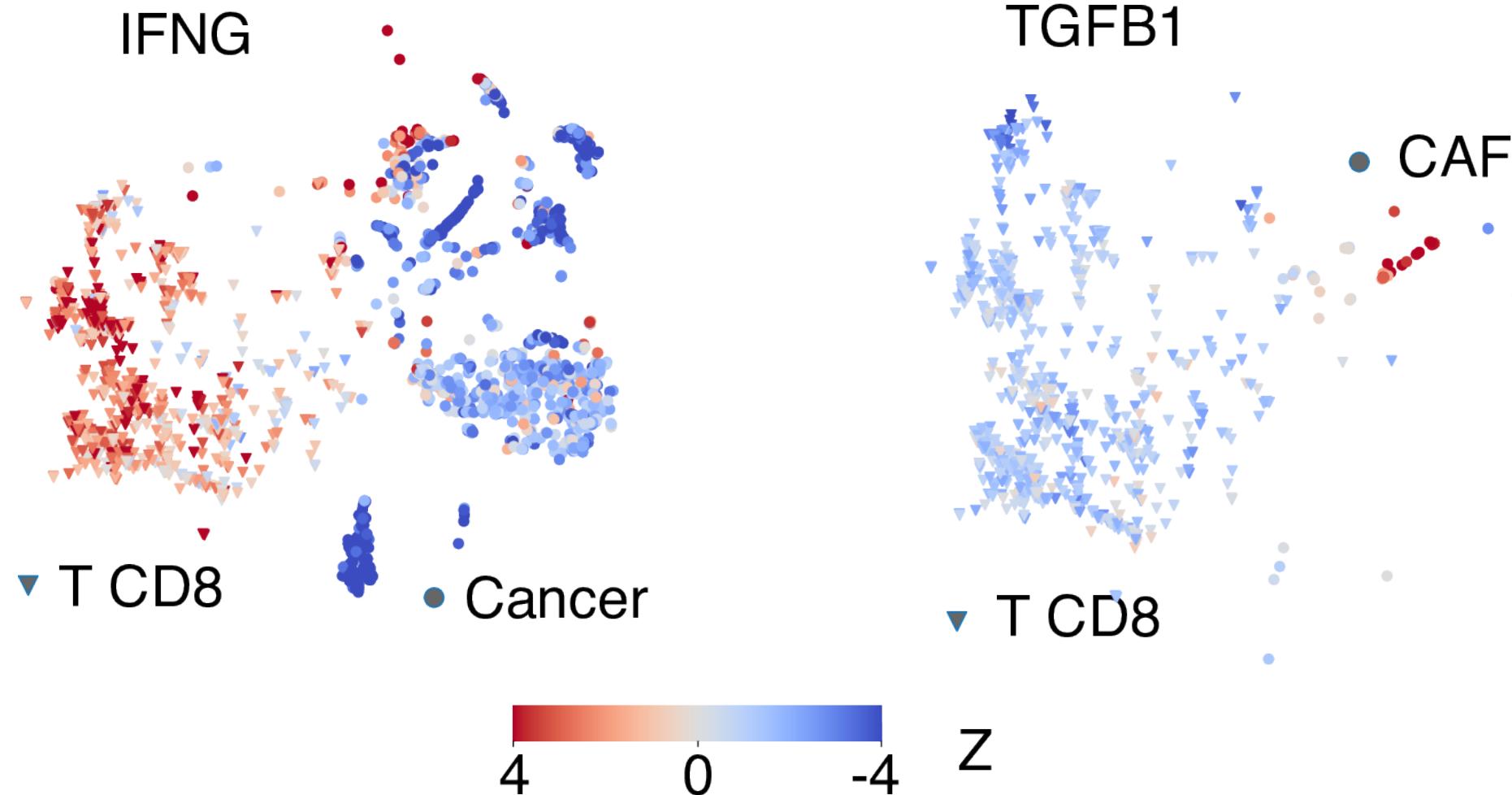
$$\text{input} = a_1 s_1 + \dots + a_n s_n$$



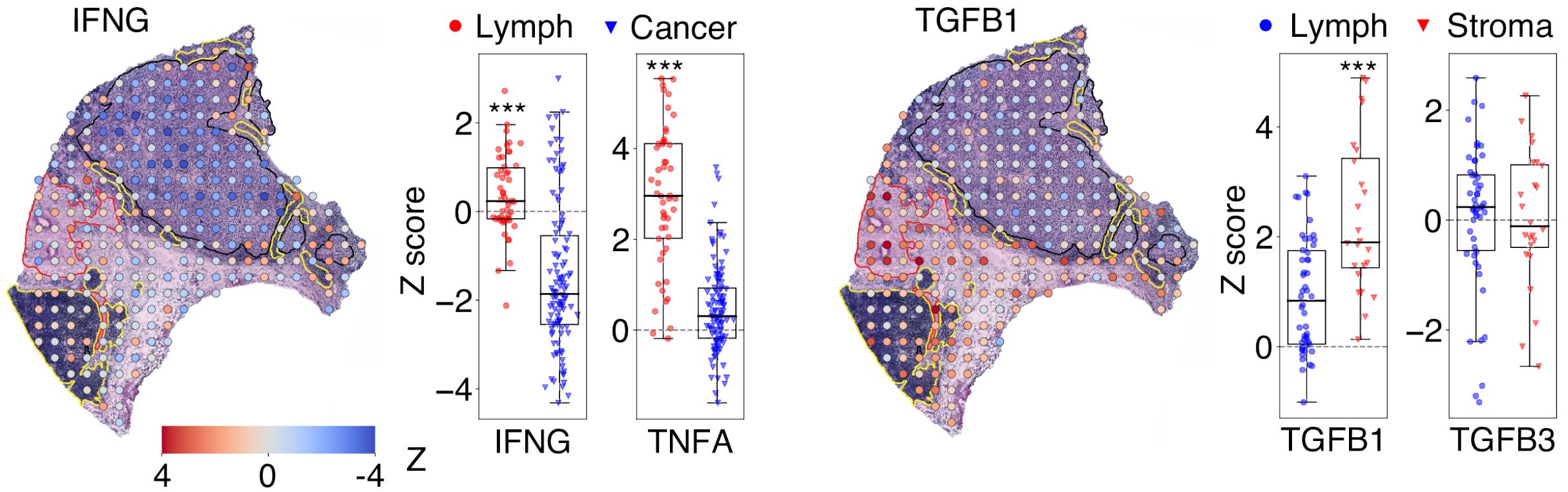
signaling molecules



# Application on Single Cell RNA-Seq



# Application on Spatial Transcriptomics



Some online demo

## Postdoc mentors



X. Shirley Liu

- Shengqing Gu
- Jingxin Fu



Kai Wucherpfennig

- Deng Pan
- Aya Kobayashi

## CSDL PIs



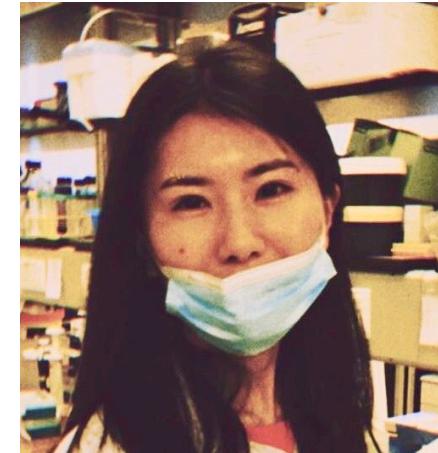
Eytan Ruppin  
Branch Chief

## Current Lab Members

Beibei Ru



Yu Zhang



Jie Yuan (expected on June, 2020)



S. Cenk Sahinalp



Sridhar Hannenhalli